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Modeling Touch Gestures to Propose Optimal Design Guidelines based on Human Performance Measures

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Abstract

Modeling Touch Gestures To Propose Optimal Design Guidelines Based on Human Performance Measures

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Touch interface has evolved into dominant interface system for smartphones over the last 10 years. This evolutionary process has been applicable not only to the smartphone, but also to small hand-held smart devices like portable game consoles and tablet devices. Even further, the most recent Microsoft Windows operating system supports both traditional point and click interface as well as touch interface for broader coverage of OS on digital devices.

Identifying factors contributing the human performance on touch interface system has been studied by wide range of researchers globally. Designers and manufacturers of smart devices with touch interface system could benefit from the findings of these studies since they may provide opportunities to design and implement better performing and more usable product with competitive edge over competitors.

In this study, we investigated factors affecting human performance on touch interface systems to establish practical design guidelines for designers and manufacturers of smart devices with touch interface system. The first group of factors is demography related variables such as gender, regions and age. The second group of factors is interaction related variables such as number of hands involved in interacting with touch system – one handed versus two handed postures. Finally and most importantly, design-related variables such as sizes, shapes or locations of touch targets are investigated.

Our main goal of this study is to identify what are the most affecting factors to human performance of touch interface systems and establish mathematical modeling among them. Developed performance modeling will be leveraged to estimate expected human performance without conducting usability testing on given touch interface system. Once demography, interaction and design related variables are given, we will be able to propose expected

performance level by inputting those variables into the established model, thus will contribute to the optimal design practice.

Touch gestures considered in this study are tap touch, move touch and flick touch, which are the most widely used touch gestures in designing and implementing touch interface system. We have recruited 259 subjects from 4 major metropolitan areas across 3 different countries – New York, San Francisco, London and Paris and conducted controlled laboratory experiment.

In order to assess human performance of each touch gesture, we have defined individual performance measures of each gesture such as task completion time, velocity, throughput introduced by Fitts' law (Fitts', 1954), variance/accuracy ratio introduced by Chan & Childress (1990), accuracy or offset tendency from a desired line of target. By investigating these performance measures, we could come up with design guidelines about design specifications such as size and movement direction as well as qualitative insights on how touch gestures are different across all the factors we have gathered from the experimental setup.

Design strategies and guidelines as well as human performance modeling will contribute to develop effective and efficient touch interface systems.

Keywords: Touch, Gesture, Smart device, Human performance, Design, Guideline

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Contents

List of Tables

List of Figures

Chapter 1. Introduction

1.1 Background

With the introduction of Apple's iPhone to the digital mobile device market in the year of 2007, touch interface became the dominant mode of usage for smartphones ever since. Touch interface has pros and cons compared to traditional point and click interface system. The benefits of using touch interface system are on its intuitiveness and direct manipulation of interface elements thus no inherent system lag between input and output. Without having to transform the actual movement input signal from input devices, it becomes more tangible and easier to use for users of smart devices. In more recent years, Microsoft launched Windows operating system which supports both traditional point and click interface as well as touch interface to provide broader coverage on smart device tiers.

While touch interface has become the most commonly used interface system in our daily lives, series of researches around touch gestures and designing touch interface system have been conducted over the last decades (Karlson, Bederson, & Contreras-Vidal, 2008; Perry & Hourcade,2008; Roudaut, Huot, & Lecolinet, 2008; Trudeau et al., 2012; Bi, Smith and Zhai, 2012).

Bi, Smith and Zhai (2012) and other researchers tried to leverage Fitts law (Fitts, 1954) to explain the behavioral performance of touch gestures especially when it involves reciprocal movement in touch gestures like move touch. Understanding the characteristics of touch gestures in terms of performance is critical since it provides valuable information for system architects and designers when they aim to implement most efficient and easy to use touch interface system.

In this study, we will investigate the three most commonly used touch gestures – tap touch, move touch and flick touch to understand what are the variables most affecting the performance of each gesture. Thus, we will start defining experimental variables which are assumed to have some impact on touch gestures, also define performance measures we can investigate their effect respectively. From this, we will be able to suggest optimal design guidelines and strategies for touch interface implementation for enhanced performance as well as predictive modeling of human performance.

1.2 Research questions

This study aims to answer the following research questions for better understandings on the three major touch gestures.

Research questions on tap touch

Research question 1 : What are the variables affecting the performance measures defined and how much are they contributing?

Research question 2 : What is the design strategies and guidelines for optimal tap touch gesture implementation in term of human performance?

Research questions on move touch

Research question 1 : What are the variables affecting the performance measures defined and how much are they contributing?

Research question 2 : What is the design strategies and guidelines for optimal move touch gesture implementation in term of human performance?

Research questions on flick touch

Research question 1 : What are the variables affecting the performance measures defined and how much are they contributing?

Research question 2 : What is the design strategies and guidelines for optimal flick touch gesture implementation in term of human performance?

1.3 Document Outline

This dissertation consists 6 chapters including this introductory chapter. In chapter 2, previous researches will be reviewed in various areas of topic such as, 1) gestures used in touch interface design, 2) how people hold mobile devices, 3) considerations in designing for thumbs, 4) touch target size guidelines suggested, 5) studies on estimating touch target sizes, 6) human performance models, 7) human performance by gender and age, 8) researches on thumb-based touch interactions, 9) models of human motor control

From chapter 3 to chapter 5, we will be looking experimental setup and the results for tap, move and flick touch. Each chapter will include: 1) introduction - describes the background, motivation and research questions of the experiment, 2) method - shows how experimental setup prepared such as demographic information of participants, experimental constraints and variables, 3) data analysis - describes how raw data managed and prepared for further analysis including outlier removal process, 4) result - consist of normality test of defined performance measures, followed by ANOVA analysis to identify most affecting variables. Linear regression model is presented for performance validation, 5) conclusion - summarizes the experimental result and provide design strategies and guidelines for optimal design process.

Lastly, chapter 6 consolidates all findings/recommendations from each experiment and suggests design strategies and guidelines for three touch gestures.

Chapter 2. Literature reviews

2.1 Potential variables affecting touch interface

In this section, we will review potential variables which may affect the usability of touch interface systems. Table 2-1 summarizes these variables in three different categories – design, interaction and demography.

Design variables include location, shape and size of touch target elements which are all interface design elements under the control of designers of the system. As touch interfaces naturally require the presence of touch objects on touch sensitive screen with varying sizes, shapes and locations, these variables are considered to have different levels of influence to the usability of touch interface system of hand-held devices.

Interaction variables are related to human behavioral characteristics when interacting with touch interface system of hand-held devices. Various gestures were implemented in touch interface systems of hand-held devices since the introduction of iPhone. As some of the gestures are more commonly used and well accepted than more complex or less intuitive ones, selecting right gestures for specific interface design could affect the usability of touch interface system of hand-held devices. Handedness could also be a contributing factor to the usability of touch interface system of hand-held devices. For example, if we allocate critical touch elements for a certain task mostly either one side of touch screen, it may degrade the usability of left handed or right handed users.

Lastly, we can expect performance will vary according to demographic variables such as age, regions and gender

All these variables are potential candidates which may or may not contribute usability of mobile touch interface system and will be covered in detail in the following sections. In this study, it will be investigated in detail which variables have the most contribution to the usability of mobile touch interface system for selected gestures used for experimental setup for this study.

Table 2-1 Variables may affect usability of mobile touch interface system

Design	Interaction	Demography
Target location	Gesture	Age
Target shape	Handedness	Region
Target size	Holding method	Gender

2.2 Gestures used in touch interface design

When Apple's iPhone was first introduced in 2007, it was considered as a revolutionary advancement of touch interface design. Due to intuitiveness and ease of use of iPhone, it quickly became the industry standard for touch interface design and implementation.

Wroblewski (2010) suggested a comprehensive set of gestures which can be applied to commonly used operating systems with mobile touch interface system such as iOS, Android, Windows mobile, Windows and OSX. He defined 10 core gestures as in Figure 2-1 which are used to define major user actions as in Table 2-1.

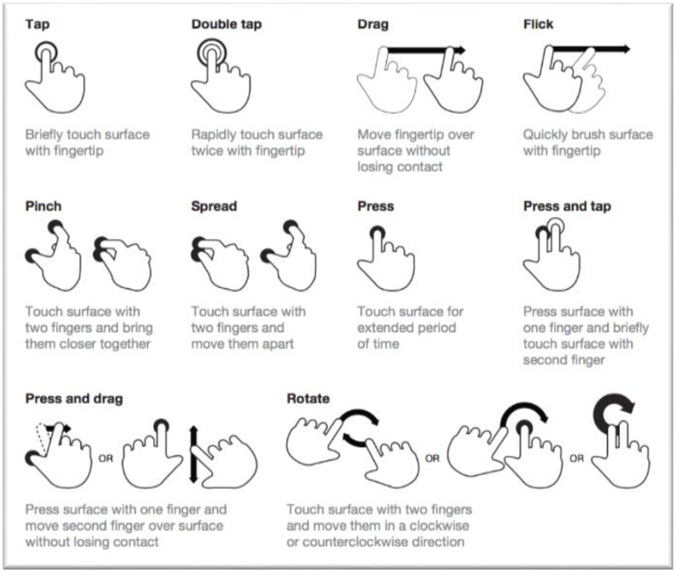

Figure 2-1 Core touch gestures (Wroblewski, 2010)

In this study, we choose tap, drag(or move) and flick touch gestures for investigation after investigating Table 2-2 since those are the most commonly used core elements of touch gestures for major user actions. If we get deeper understandings on those gestures, we could come up with design principles or strategies targeting better usability covering wide range of user actions in the most common context of use.

Table 2-2 Major user actions (Wroblewski,2010)

User action	Gesture	Description
Change mode	press	Touch surface for extended period of time
Open	double tap	Rapidly touch surface twice with fingertip
Select	tap	Briefly touch surface with fingertip
Adjust	press and drag	Press surface with one finger and move second finger over surface without losing contact
Bundle	press and tap, then drag	Touch first object while second finger taps other objects, the move selected objects by dragging first finger
Delete	drag (across item or off-screen)	Move fingertip over surface without losing contact
Duplicate	tap (source and destination)	Touch object, then touch elsewhere on surface
Move	drag (and drop)	Move fingertip over surface without losing contact
	flick	Quickly brush surface with fingertip
	press and tap	With one finger on object, touch elsewhere on surface with second finger
Display commands	press	Touch surface for extended period of time
	press and tap	Press surface with one finger and briefly touch surface with second finger
	double tap	Rapidly touch surface twice with fingertip
Move through list	two-finger drag	Move to previous/next item in list
Pan	drag hand	Move fingers and palm of one hand over surface without losing contact
Scroll	drag	Move fingertip over scrollbar without losing contact
	press	Touch scrollbar for extended period of time
Scroll (fast)	flick	Quickly brush surface with fingertip in the direction you want to scroll
Scroll (fast)	tap	Briefly touch surface with fingertip when a scroll is in progress
Scrub	drag	Move fingertip over scrollbar without losing contact

Press(or tap) appears almost all major user actions as basic touch element which means has the most impact on the usability of mobile touch interface system. Drag(or move) also appears frequently but not as much as tap. Combining these two basic touch element could produce most of major user actions' gestures. Flick has the least presence among the three gestures, it will complement actions like scroll which is one of the major use actions in mobile touch interface system. In this study, we will call these three touch gestures as tap, move and flick gestures throughout the rest of the sections.

2.3 How people hold mobile devices

People carry mobile devices with them everywhere they go – while walking, standing, riding a bus, in a train, or doing just about anything. Since touch mobile devices are not like desktop computers which are fixed in a single location in most cases, it provides wide variety of context of use due to its mobility factor.

There have been many discussions how people hold their mobile devices (Clark, 2013; Diaz, 2013). Hoober (2013) however, questioned some of their assumptions and established new assumption that people will prefer holding mobile devices with one hand. In order to validate this assumption, Hoober observed 1,333 mobile users on the street, at airports, at bus stops, in cafes, on trains and buses. At a higher level, 780 people were actively engaged in using or interacting with their mobile devices – scrolling, tapping, typing and other gestures to enter input. The rest are just merely listening to, looking at or talking on their mobile devices.

Figure 2-2 shows the visual breakdown of this high-level finding. It shows passive engagement to mobile devices like listening, talking or looking is about 40% of total observation, other 60% are actively involved in interacting with their mobile devices. From the 60% of usage groups, 29% of them are using one hand with thumb, 21% are using one hand holding the device and the other hand to interact with the device.(he called it as cradled posture), 9% are holding devices with two hands. For one handed use, 67% of them are using their right thumbs, and other 33% use their left thumbs. Thus one handed and cradled postures consist about 80% of active interactive sessions which this study will further investigate their characteristics to suggest best design strategies and practical guidelines.

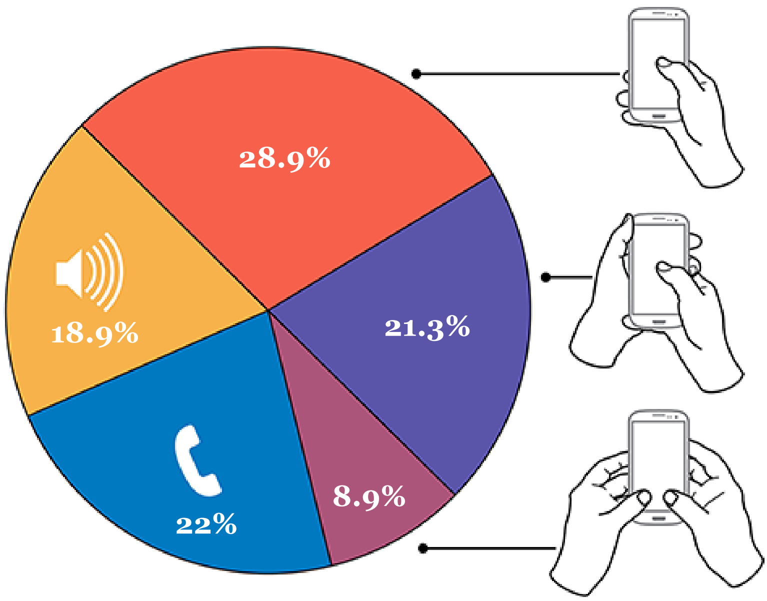

Figure 2-2 Summary of how people hold and interact with mobile phones

In the recent trend of large mobile touch devices more than 4 inches (Hurff, 2014), it is worthwhile to note that even one handed posture could produce a different range of motion on a touch screen according to the placement of thumb joint location relative to touch screen. Recent researches around thumb-based input have been conducted with a focus on usability and performance incurred by the limited range of motion of thumbs (Karlson, Bederson, & Contreras-Vidal, 2008; Perry & Hourcade, 2008; Roudaut, Huot, & Lecolinet, 2008; Trudeau et al., 2012). However, it is interesting to note that thumb-based input is still most preferred mode of use while using mobile devices if usability and performance issue can be mitigated (Karlson et al., 2008).

Figure 2-3 illustrate this as it shows lower thumb joint location provides green thumb access zone-where thumb can reach without any extra effort. On the lower left corner of the screen while higher thumb joint position would produce higher green thumb zone area. This is specifically could be an issue when interacting large devices which are larger than 4 inches of display. Smaller devices would have less variability on thumb joint location even considering hand anthropometric differences. In this study, we assumed that this factor is fixed because the device used for the experiment is smaller than 4 inches thus we expected less variability due to different positions of thumb join location. It would be a good follow-up study topic to investigate the effect of the location and hand size anthropometric measures.

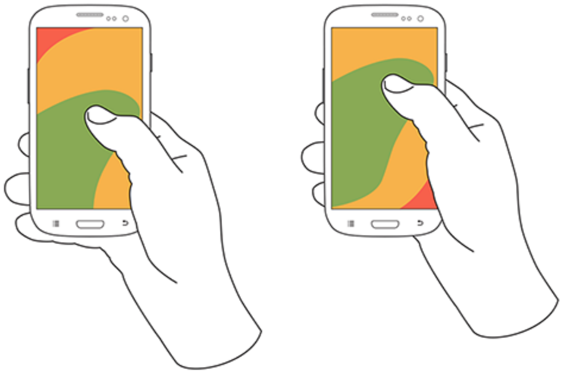

Figure 2-3 Two methods of holding a touchscreen phone with one hand.

It is noticeable that around 70% of usage among cradled postures, they use their thumbs while using another hand to support the device, and 30% of them are using their index finger to interact with their mobile devices. In Figure 2-4, it shows the green access area between the two different postures, one with index finger doesn't have the yellow area, while one with thumb shows the yellow area in the upper left and lower right corners. This means even with cradled postures, if they are using thumbs to interact with touch screens, it is still constrained by the limit of the range of motion of thumb. Though Hobber's observation showed 70% of usage in cradled posture use their thumb, we choose to use the setup of using the index finger to compare and investigate the amount of usability or performance discrepancies between thumb-based and index finger based input methods.

Figure 2-4 shows two different variations of cradled postures. Both postures use one hand for supporting the device, the other hand with thumb or index finger to interact with the device. As it is depicted as a green and yellow zone, thumb based interaction still has a less reachable area on top left and bottom right corner of the display(for right handed user) while index finger based interaction doesn't have such restricted area.

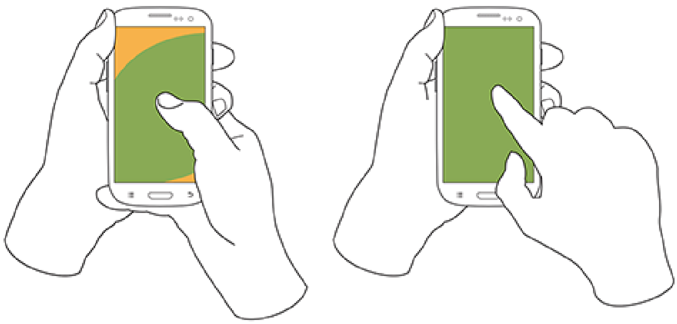

Figure 2-4 The two methods of cradling a mobile phone

2.4 Design for thumbs

As noted earlier, the thumb-based input method is still most preferred mode of use using touch interfaces despite its inherent usability and performance constraints (Karlson et al., 2008). Designing for thumbs means building interfaces that are the most comfortable to use within our thumb's natural, sweeping arc (Hurff, 2014). This design goal becomes more difficult to achieve when the size of mobile devices become larger. Figure 2-5 shows this aspect of usability issue across the different sizes of iPhones. This conceptual heat map is the best guess of the area where reachability of thumbs on a different area of the screen on varying sizes. As it shows, the natural reach zone becomes smaller as device or screen sizes become larger.

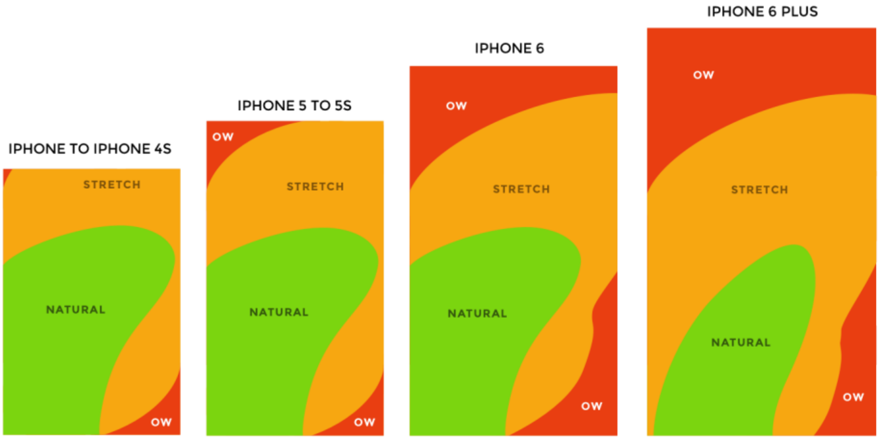

Figure 2-5 Thumb zones comparison among iPhones (Hurff,2014).

In this study, we will not focus on the usability degradation across the different screen or device sizes to keep our research under the manageable scope. We will investigate mathematical modeling of touch gesture performance measures to predict performance measures on different locations of the screen with given device size.

2.5 Touch target size guidelines

Touch targets should be big enough to receive input from finger with less or no errors and with the best performance such as task completion time to avoid fat finger issue (Cockburn et al., 2012; Sasangohar et al., 2009; Lee et al., 2009). Wroblewski (2010) consolidated touch interface design guidelines from multiple manufacturers of mobile touch devices such as Apple, Nokia, Google and Microsoft. Figure 2-6 shows the sample of their touch interface design guidelines.

In the iPhone Human Interface Guidelines, Apple recommends a minimum target size of 44 pixels wide 44 pixels tall. Since physical pixel size can vary by screen density, actual target size in physical size can be calculated if we know device's PPI(pixel per inch) information.

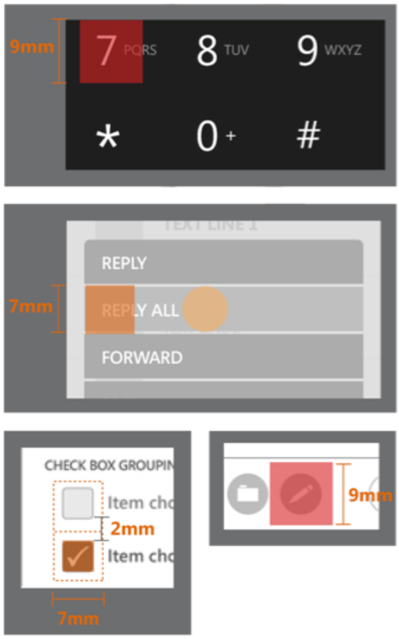

Figure 2-6 Touch interface design guidelines

In the Windows Phone UI Design and Interaction Guide, Microsoft suggests: a recommended touch target size of 9mm/34px; a minimum touch target size of 7mm/26px; a minimum spacing between elements of 2mm/8px; and the visual size of a UI control to be 60-100% of the touch target size. They also suggest touch targets can be larger than 9mm if: the UI element is frequently touched; the result of a touch error is severe or really frustrating; the UI element is located toward edge of the screen or difficult to hit; or when the UI element is part of a sequential task –like using the dial pad.

Nokia's developer resources suggest that touchable interface elements should not be smaller than the smallest average finger pad, that is, no smaller than 1 cm (0.4") in diameter or a 1 cm × 1 cm square. According to the them, minimum target sizes for a finger usable UI element are: 1) 7 x 7 mm with 1 mm gaps for index finger usage, 2) 8 x 8 mm with 2 mm gaps for thumb usage, 3) list type of components should have minimum of 5 mm line spacing. They also suggest that the width of a finger limits the density of items on screen. If the items are too close, the user will not be able to choose a single one.

The Ubuntu Designing for Finger UIs documentation states the minimum size of buttons and other interface elements should be determined by the size of an adult finger(diameter of 16mm to 20mm- Dandekar, Raju & Srinivasan, 2003). When interacting with a touchscreen, users will prefer to use the pad of their finger rather than the tip. The pad of the finger is slightly narrower than the full width of the finger: 10-14mm. The fingertip is smaller - 8-10mm wide - but more awkward to use than the pad of the finger. In general, they suggest interface elements should be no smaller than 1cm (0.4").

All these industrial touch interface design guidelines fall into the similar range of sizes with slight differences in values though they don't provide details why they selected certain ranges of touch target sizes with scientific evidence. Parhi, Karlson & Bederson (2005) looked in detail at the interaction between target size and task performance in single- and multi-target tasks, recommended target sizes at least 9.2 mm for single-target tasks and 9.6 mm for multi-target tasks. They tried to identify optimum touch interface sizes by comparing error rates of varying touch target sizes in combination with personal preferences. In our study, we will be focusing on performance measures in predicting optimal target size rather than error rate to establish design guidelines focusing on producing best performance measures rather than least error rates. This result can be compared to validate if there is an in-between range of guidelines to capture both aspects of usability concerns.

2.6 Estimating touch sizes

Finding the right balance between visual simplicity and information density of touch interface system has been debated as a difficult topic to conclude (Wroblewski, 2014). It is challenging because if it is too simple or too sparse, people may appreciate the simplicity at first sight, but they may complain about not having the information amount enough not to require them navigate into the menu more frequently. Using right dimension of screen elements will play a crucial role in balancing between visual simplicity and information density of digital system, especially touch interface system.

Number of studies have been conducted to find appropriate target sizes of various devices from hand-held touch devices to desktop sized touch displays. Brewster (2002) established a hypothesis that presenting sound feedback on touch buttons would increase their usability thus allow target sizes to be reduced. He empirically showed that about 50% of the reduction in target size with the same level of usability could be achieved in the controlled experimental setup. It is an interesting finding that augmenting proper sound feedback could contribute better usability thus allowing reduction in size, but he also admitted that mobile devices are to be used in any context of use such as outdoor, walking, riding vehicles, or talking to someone so sound feedback may not work as effectively as in the controlled lab environment. Mackenzie & Zhang (2001) investigated the effect on typing rates with different sizes of touch qwerty keypads(6.4x6.4mm and 10x10mm). They found no effect on touch sizes. It showed that maintaining the same qwerty layout on touch qwerty will require no educational session for users, while randomized presentation drastically reduced the typing rate proving randomized layout should not be used for touch qwerty keypad. Mizobuchi et. al. (2002) conducted an experiment to understand minimum required target size on a small display device using a stylus pen. Sears & Zha (2003) tried to understand the effect of keyboard sizes and tasks when using stylus pen on small touch devices. They measured data entry rates(as wpm) for different keyboard sizes, and found no significant effect based on keypad sizes. They claimed that their research proves that small qwerty keypads on small touch devices will produce a similar level of data entry rates. But they didn't provide the exact size limits of touch interface elements.

Colle & Hiszem (2004) began to suggest the size limit of touch interfaces that 20x20mm sized touch keys demonstrated the lowest error rates among other sizes(10~20mm). They recommended to use 20x20mm sized keys for touch kiosks which may not be directly applicable for small hand-held touch devices.

More recently, Parhi & Karson (2006) conducted two experiments to suggest optimal touch target sizes for discrete and serial input tasks. They identified that there was no significant difference in error rates for target sizes ≥ 9.6mm in discrete tasks and target sizes ≥ 7.7mm in serial tasks. Along with subjective ratings and the findings on hit response variability, they suggested 9.2mm for discrete tasks and targets of 9.6mm for serial tasks to be used for one-handed thumb interaction for performance and preference. However, they only focused on one-handed thumb interaction, not suggesting index finger interaction which is also popular usage setup for mobile devices. In our study, we have conducted serial tapping tasks for one-handed thumb interaction and cradled interaction which is index finger interaction.

Parhi & Karlson used error rates, individual preference ratings, and hit response variability to suggest optimal touch sizes. On the contrary, we will be using the distance from the center of target touch (accuracy measure) to suggest optimal touch sizes and validate if it confirms the result of Parhi and Karlson's. This way, we will be able to prove that in order to suggest optimal touch sizes, we will only need to measure accuracy from the center of touch targets.

Park & Han (2010) measured success rate and input offset to understand the behavior of one-handed thumb touch interaction.

They also showed that touch key sizes and relative locations on touch display had affected the success rate and input offset. Instead of suggesting optimal touch key sizes, they implemented simulation algorithm to suggest the optimal touch recognition area while keeping the physical size of touch keys the same to get better touch accuracy. According to the result of their simulation, for 90% of touch accuracy, value of x and y offset were calculated for touch key sizes of 4 mm and 7mm. For 96% of touch accuracy, they also calculated x and y offset values for 4mm, 7mm and 10mm. We will also investigate the offsets and touch tendency of serial touch tasks to suggest optimal design strategies.

2.7 Human performance models

Understanding human motor performance plays a critical role in designing and developing usable human-computer interface systems. Specifically, quantifying rapid aiming movements with hands, arms, and fingers has important consequences on HCI design (Schedlbauser, 2007). Human performance can be evaluated by using three criteria—the quality of task outcomes, the accuracy of movement trajectory, and the efficiency of the human mechanism behind the manifest movement (Schmidt & Lee, 2011). This study focuses on the quality of task outcome since it captures overall performance of human motor systems. One of the earliest and most broadly applied engineering model to assess human motor performance is Fitts' law (Fitts, 1954). In essence, Fitts' law provides a predictive model to estimate the time to take to point one position with a stylus to another one based on the sizes and distance between the two targets. Since the introduction of the original Fitts' law model, there have been numerous researches on variations of Fitts' law to adapt to different types of pointing tasks such as a mouse, or joystick or touch sensitive devices. Input tasks using different input devices have been empirically validated (MacKenzie & Soukereff, 2003; Mcguffin & Balakrishnan, 2005; Hinckley, K., Jacob, R., & Ware, C.,2004).

Fitts' law typically defined as :

$$\boldsymbol{T = a + b\log_2(\frac{A}{W} + 1)} \qquad \textbf{Equation 2-1}$$

where T is the average time taken to complete the movement, A is the distance from the starting point to the center of the target, W is the width of the target, and a and b are empirical constants reflecting the efficiency of the pointing system. Since its simplicity and strong predictive power, Fitts' law has been the HCI research basis of quantifying the performance of human motor systems. Card, English & Burr (1978) applied Fitts law to compare text input performance of four different input devices. Mackenzie & Zhang (2001) used Fitts' law to evaluate the performance difference between qwerty like soft keyboard versus randomized soft keyboard. Bi, Smith & Zhai (2012) utilized movement time estimator from Fitts' law as an objective function in their optimization problem of designing multilingual keyboards. Zhai & Kristensson (2012) also leveraged Fitts' law as efficiency measure while they are evaluating the performance of gesture-based qwerty input method.

Table 2-3 Taxonomy of quantitative prediction models for mean movement time along one, two, or three dimensions either along a straight line or a trajectory

Model	Estimator of Movement Time(T)	Applicability
Generalized Fitts' Law	$a + k\log_2\left(\frac{D}{W_e} + \varepsilon\right)$	1-dimensional direct pointing tasks with effective width
MacKenzie-Buxton Bivariate Pointing	$a + k\log_2\left(\frac{D}{min\left\{\frac{H}{\sin\varphi}, \frac{W}{\cos\varphi}\right\}} + \varepsilon\right)$	2-dimensional direct pointing tasks
Accot-Zhai Bivariate Pointing	$a + k\log_2\left(\sqrt{\left(\frac{D}{W}\right)^2 + \eta\left(\frac{D}{H}\right)^2} + 1\right)$	2-dimensional direct pointing tasks
Oel et al. Power Model	$(a \times W^b) \times A^{c+d\times\log_2 W}$	small targets
Meyer's Law	$a + k\sqrt{\frac{D}{W}}$	1-dimensional pointing tasks
Kvålseth's Law	$a + b\left(\frac{D}{W}\right)^c$	1-dimensional pointing tasks
Accot-Zhai Goal Crossing	$a + k\frac{D}{W\log_e 2}$	Movement along a straight tunnel
Accot-Zhai Narrowing Tunnel	$a + \frac{D}{W_2 - W_1} \times \log_e\left(\frac{W_2}{W_1}\right)$	Movement along a narrowing tunnel
Accot-Zhai Circular Tunnel	$a + b\frac{2\pi R}{W}$	Movement along a circular tunnel trajectory
Accot-Zhai Steering Law	$a + b\int_{\varsigma}\frac{1}{W(s)}ds$	Movement along a curved tunnel trajectory
Grossman-Balakrishnan Trivariate Pointing	$a + k\log_2\left(\sqrt{f_W(\theta)\left(\frac{A}{W}\right)^2 + f_H(\theta)\left(\frac{A}{H}\right)^2 + f_D(\theta)\left(\frac{A}{D}\right)^2} + 1\right)$	3-dimensional pointing task (extension to Accot-Zhai bivariate pointing)

Even though original form of Fitts' law has been leveraged in many HCI research, there have been many efforts to improve the predictive power to fit more general use cases to overcome the limitation and assumptions from its original experimental setup which is a simple one-dimensional pointing task using a stylus. Table 2-3 shows various models of Fitts' law that have been developed to propose models for various tasks environments. (Schedlbauer, 2007)

Oel et al. (2001) evaluated some of the models in Table 2-3 by comparing their correlation coefficients using experimental data. Table 2-4 summarizes their findings and rankings by R^2 values. R^2 represents the coefficient of determination in a multiple regression analysis. R^2 quantifies the percentage of explained variability in the model. According to their findings, Oel et al. & Kvålseth have the best fit with the observed data points. Original Fitts' law ranked the lowest of them all, though it still provides good estimator considering the simplicity in its form.

Table 2-4 Ranking of models by Oel et al. (2001).

Model	R^2	Rank
Oel et al. Power Model	0.9664	1
Kvålseth's Law	0.9154	2
Generalized Fitts' Law(ε=1, MacKenzie)	0.9011	3
Generalized Fitts' Law(ε=0.5, Welford)	0.8951	4
Generalized Fitts' Law(ε=D/W, Fitts)	0.8839	5

The tasks in touch interaction can be decomposed into a set of discrete movements, such as tapping, dragging, radial pointing (Cockburn et al., 2012), flicking and scrolling (Tu et al., 2012), tilting

(MacKenzie & Teather, 2012) or a combination of them. Fitts' Law is a classic theory to describe the relationship between movement time and index of difficulty, or indirectly, speed and accuracy. Typically, it applies to evaluating performance in tapping and dragging for touch interaction (Forlines et al., 2007; Henze & Boll, 2011; Perry & Hourcade, 2008; Sasangohar et al., 2009). Fitts' Law is also extended to evaluating tasks beyond the original reciprocal-tapping (Bi, Li, & Zhai, 2013; Kim & Jo, 2012; Kim & Jo, 2015; Murata, 1999; Murata & Iwase, 2001; Song, 2012; Zhai, Kong, & Ren, 2004).

As we can see from aforementioned research around Fitts' law, many of them have been focusing on interaction using a stylus even on touch interfaces. Recently, there has been growing interest in understanding characteristics of finger touch interactions – especially fat finger problem (Cockburn et al., 2012; Sasangohar et al., 2009; Lee et al., 2009).

Bi et al. (2013) suggested FFitts law which is modified Fitts law dedicated to explaining the behavior of finger touch gestures. In order to accurately model finger input, they proposed dual distribution hypothesis to interpret the distribution of endpoints of finger input. They hypothesized that the endpoint distribution is a sum of two independent normal distributions. One reflects the relative touch precision governed by the speed-accuracy tradeoff in the human motor system, and the other reflects the absolute precision of finger touch independent of the speed-accuracy tradeoff effect. Their hypothesis can be utilized to model human touch behavior. However, their experimental setup to validate their hypothesis was using tap target size no larger than 7.2mm which is fairly small tap target as generic tap targets for smartphones. Also they conducted an experiment using only cradled posture which will give no insights on one-handed postures when using touch interface. Park & Han (2010) tried to identify optimal touch key sizes which yield best success rates of tap touch tasks. They used one handed posture to evaluate thumb-based touch gestures.

For a move task, rapid aimed movement coordinates two separate controls—the one for acceleration to gain desired movement Amplitude (A), and the other for deceleration to constrain motion within certain Width (W) (C. L. MacKenzie, Marteniuk, Dugas, Liske, & Eickmeier, 1987). Movement Time (MT) integrates the result of both controls (Turvey, 1977). Throughput(r) measures the efficiency of these controls. To put r differently, it is a measure of the efficiency of interaction between actor and environment (Bootsma, Fernandez, & Mottet, 2004), remaining relatively invariant throughout a range of task conditions (Fitts, 1954). Since r remains relatively invariant, it is considered to indicate an intrinsic performance. Equation 2-2 represents throughput(r) as described by Fitts (1954) using variables of A, W, and MT. Note that W and A are independent variables to be controlled, to which MT will respond as a dependent variable.

$$\boldsymbol{Th(MT;W,A)=\frac{ID}{MT}=\frac{\log_2(\frac{A}{W}+1)}{MT}\approx r} \qquad \textbf{Equation 2-2}$$

Throughput may vaguely translate into speed-accuracy tradeoffs by observing the inverse relationship between the index of difficulty

(ID) and movement time(MT). In fact, this view of tradeoff relationship is not the most accurate, because ID indirectly addresses accuracy only if A is fixed, and speed is not expressed by velocity. Besides, W is not a unique way to represent accuracy. Alternatively, some authors used different forms of speed and accuracy to express the tradeoffs; speed is measured by average velocity (A/MT), and accuracy is measured by the within-subject standard deviation of A. It was observed that different control mechanisms cause the speed-accuracy relationship to be either logarithmic or linear (Jagacinski & Flach, 2003; Meyer, Abrams, Kornblum, Wright, & Smith, 1988; Schmidt & Lee, 2011). Researchers also investigated individual biases on speed and accuracy (Fitts & Radford, 1966; Zhai et al., 2004). Empirical findings suggest that throughput remains constant, regardless of bias (MacKenzie & Isokoski, 2008).

Unlike speed, accuracy measures further complicate the investigation, requesting additional consideration (MacKenzie, Kauppinen, & Silfverberg, 2001; Zhai et al., 2004). The ISO 9241-9 standard recommends that researchers use effective width (W_e) as a substantive proxy for accuracy, rather than nominal target width (W). Technically, effective width (W_e) relies on the standard deviation of end points within a block of samples. The caveat here is that by blocking we tend to lose information. More critically, blocking involves a decision making as to what constitutes a unit of block.

Chan & Childress (1990) showed that variance of human machine noise is proportional to the square of human machine output velocity as depicted in equation 2-3 where σ_n represents human machine noise, v as human machine output velocity, and K as empirical constant. Square root value of K in this equation is leveraged as speed accuracy ratio of tap touch experiment.

$$\boldsymbol{\sigma_n}^2 = \boldsymbol{K v}^2 \qquad \textbf{Equation 2-3}$$

They derived this equation from cross-over model (McRuer & Krendel, 1959; McRuer & Jex, 1967; McRuer, 1980), Fitts' law (Fitts & Peterson, 1964; Fitts, 1954) and information transmission results of Elkind (Elkind & Forgie, 1959; Elkind & Sprague, 1961). Even though these models were initiated from different approaches, Chan & Childress proved that they all could be derived into equation 2-3. This is another form of describing speed-accuracy trade-off which means the ratio of human machine output velocity and human machine noise variance remains constant.

2.8 Human performance by gender and age

In order to explain the human performance degradation by age, two factors have been referenced by many researchers. First, older population take a longer time to complete a movement task thus result in a longer completion time. Second, older population spend more time decelerating their movement than accelerating.

Walker et al (1997) took into more detail to categorize the four factors known as causes of age-related differences in movement performance.

Factor 1 is "increased noise-to-force ratio". Age-related slow movement is based on two assumptions, one is signal noise is increased while aging. Noise in muscle signal is defined as a random and unintentional error happens while brain transmits the movement signal to muscle. It is believed that this noise increases as one ages, thus result in longer movement time due to noise in signal (Fitts,1954). The second assumption is this noise will increase when required force for a movement increases. Usually, rapid movement requires greater force, thus increases the noise in muscle signal. Welford (1981) suggested that as one age, the noise-to-force ratio increases, thus older population produce more noise when they apply the same level of force as a young population. If this ratio increases, they move slowly in order to maintain the same level of accuracy as a young population.

Factor 2 is "less efficient perceptual feedback" which means the efficiency of the visual processing system of the older population is not good as younger generation (Cremer & Zeef, 1987; Verillo & Verillo, 1985). This could also contribute the slowness of movement.

Factor 3 is "strategy difference". This is about how each age group plans their movement differently in terms of speed and accuracy. The Older population is more error averse than younger group, thus move slower than younger group (Goggin & Stelmach, 1990). Speed-accuracy trade-off happens in all age groups when they perform a rapid movement, older group put more stress on accuracy than speed, thus moves slowly.

Factor 4 is "ability to produce force" as one easily notice, as one gets older, it will require more energy to produce the same level of force as the younger group. This could also lead to a slower movement. In this study, we will investigate to see if these age-related factors are present in our experimental result and how they could be interpreted in designing usable touch interface system when considering different age groups.

There has been researches around performance impact on touch movement task imposed by gender. It is known that speed of simple movement tasks does not vary with sex for children usually prior to puberty (Baken, 1986; Spreen & Gaddes, 1969). It is interesting to note that if several different movements have to be made rapidly, female children are usually faster than male children (Denckla, 1973, 1974). This advantage on a female is also found in adult, but less consistent than in children (Baken, 1986; Lomas, 1980; Lomas & Kimura, 1976; Tiffin & Asher, 1948). For adults, it shows that there is consistent performance advantage of male over female for the same simple movement tasks (Baken, 1986; Barnsley & Rabinovitch, 1970; Fairbanks & Spriestersbach, 1950). In our study, we will investigate if we find any of these performance difference by gender and translate into design guidelines.

2.9 Thumb-based touch interaction

Touch interface has become a major mode of interaction for mobile devices like smartphone, tablet, navigation system and game consoles. Wide applications of touch interaction have motivated interface designers to seek easy and natural interactions while maintaining equivalent, or even improved performance level (Cockburn et al., 2012). Users carry them on a daily life, and use them in various context of use – at work, while walking, driving, and even sleeping. Noticing their proximity to users, studies on physical interaction even attempt to incorporate human capabilities into input devices for performance (Klemmer, Hartmann, & Takayama, 2006). Attention to human interactive performance may date back to the seminal work of Fitts (1954) using a stylus with a circuit to count activities. The research that compare the performances of different modes of interaction have flourished in the last two decades (Douglas, Kirkpatrick, & MacKenzie, 1999; Forlines, Wigdor, Shen, & Balakrishnan, 2007; Lee & Zhai, 2009; Mack & Lang, 1989; Sasangohar, MacKenzie, & Scott, 2009; Tu, Wang, Tian, & Ren, 2012).

Particularly, thumb-based input has been highlighted recently (Karlson, Bederson, & Contreras-Vidal, 2008; Perry & Hourcade, 2008; Roudaut, Huot, & Lecolinet, 2008; Trudeau et al., 2012), with a focus on its problems in usability and performance. Nevertheless, surveys and field studies revealed that mobile phone users still preferred to use thumb-based input if usability issues could be overcome (Karlson et al., 2008), and this preference continues with merging trends of over-four-inch screens for mobile phones (Hurff, 2014). Pascoe et. al (2000) also showed that interface design that allows one-handed operations can offer a substantial benefit by freeing a hand for the variety of physical and demands for attention common to mobile activities. However, the preference to thumb-based input is not fully realized in daily use, because the problems in usability and performance have not been adequately resolved through design solutions. Known issues in thumb interactions are summarized in Table 2-5. Although several design solutions and guidelines were proposed – such as Area cursor (Worden, Walker, Bharat, & Hudson, 1997), Bubble cursor (Grossman & Balakrishnan, 2005), TapTap (Roudaut et al., 2008), alternatives against "fat finger problem" (Yatani et al., 2008), Offset cursor (Potter, Weldon, & Shneiderman, 1988), UI components placed within easy reach of the thumb (Henze et al., 2011; Karlson et al., 2008), and recommended sizing (Apple, 2010)–the performance problems of thumb-based input have not been analyzed extensively.

Table 2-5 Usability and performance issues in thumb-Based touch interactions

Issues	Description	Related Articles
Fat finger Problem	Imprecise touch input due to the large contact area of the finger or thumb	Cockburn et al., 2012; Katre, 2010; Roudaut et al., 2008
Visual Occlusion	Restricted field of vision due to part of the finger or thumb	Roudaut et al., 2008; Song, 2012
Visual Parallax	Difference in the perceived and actual target locations arising from a tilted eye position	Potter et al., 1988;
Position Effect	Systematic performance reduction along the touch position due to postural constraints	Henze et al., 2011;
Direction effect	Systematic performance reduction along the direction of movement due to biomechanical constraints	Karlson et al., 2008; Trudeau et al., 2012
Contextual Interference	Use of non-preferred hand or walking	Bergstrom-Lehtovirta et al., 2011; Perry & Hourcade, 2008
Design Issues	Lower bound of the target size	Apple, 2010;

2.10 Models of human motor control

There has been various research efforts to come up with models to explain the process of motor control in selecting a target object. One of the earliest models proposed by Crossman & Goodeve (1983) is the iterative correction model(ICM). This model describes that human motor control is entirely based on closed loop control mechanism as depicted in Figure 2-7. According to the model proposed, human movement is composed of series of discrete sub-movements and at the end of each sub-movement, visual and proprioceptive feedback is collected to evaluate if the target is achieved or further corrective sub-movement is required. This feedback loop continues until the desired target is acquired.

Another model proposed by Schmidt et al. (1979) is impulse variability model(IVM). This model describes that human movement is consist of initial impulse transmitted to activate muscle toward the desired target with gliding motion into the target at the end without further correction is happening. Neither of these models is fully accountable for the observed behaviors of human movements to target. For example, if ICM holds true, most of human movement to acquire a target would not produce selection errors since all sub-movements should occur until the target is hit. Similarly, IVM is not supported by series of experimental observations by MacKenzie et al. (2001) and Mithal & Douglas (1996). It shows initial acceleration towards the target then followed by small corrective movements close to the target.

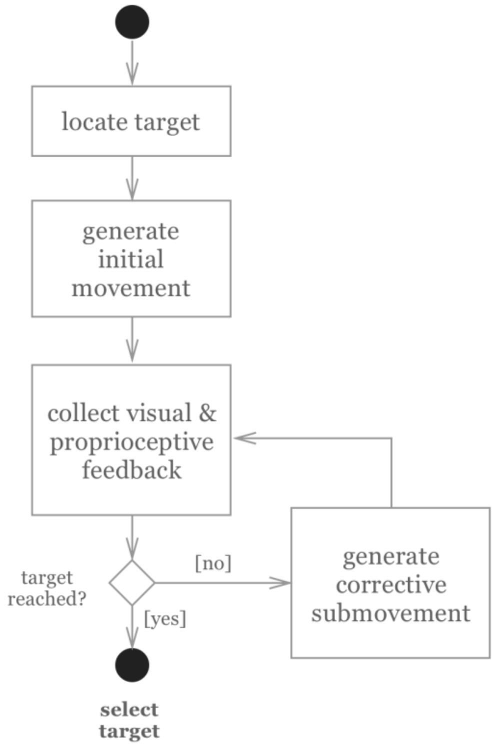

Figure 2-7 Control scheme for corrective submovements comprising an aiming task (Crossman & Goodeve, 1983)

Considering these, Meyer et al. (1988) proposed optimized initial impulse model(OIIM) which is basically hybrid of the previous two models, initial impulse to muscle dominates the rapid movement towards the target then small corrective sub-movements followed until the target is hit. It works well with the speed accuracy trade off from Fitts' law. Figure 2-8 shows these three models on time versus speed graph.

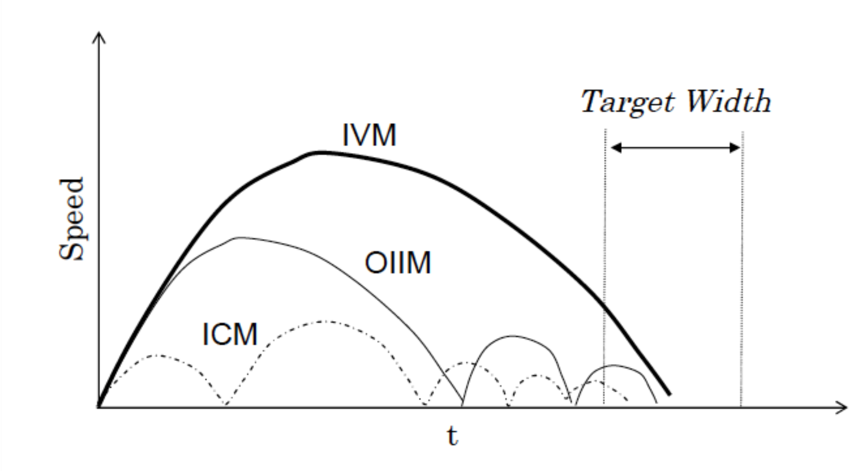

Figure 2-8 Movement velocity profile for each model of human motor control

Three models reviewed here does not include initial cognitive selection time when there are multiple targets presented.

Hick-Hyman law (Hick, 1952; Hyman, 1953) is a model based on information theory which predicts choice reaction time when there is several choices exist. It states reaction time(RT) is proportional to the entropy of the decision(H). It is given as:

$$\boldsymbol{RT_n = RT_1 + kH} \qquad \textbf{Equation 2-4}$$

where RT_n is reaction time when n equally probable choices, RT_1 is simple reaction time when there is only one choice exists. k is empirically driven coefficient, usually between 140-200msec. H, the entropy of decision, can be stated as either:

$$\boldsymbol{H = \log_2(n+1)} \qquad \textbf{Equation 2-5}$$

or

$$\boldsymbol{H = \sum_{i=1}^{n} p_i \log_2 \left(\frac{1}{p_i} + 1\right)} \qquad \textbf{Equation 2-6}$$

where n is number of equally probable choices p_i is the probability of i^{th} choice among n unequally probable choices.

Chapter 3. Tap touch experiment

3.1 Introduction

Tap touch is the most basic and widely used touch gesture in touch interface design, it is almost impossible to imagine designing a touch interface system without leveraging tap touch interaction since it is the most basic touch gesture. As touch interface paradigm is introduced in digital devices, the design of traditional controllers like buttons, knobs, or switches becomes boundless in terms of design possibility. This means designers of touch interface system could design any layout, controller or switches at a given state without having any physical limitation. However, it is also possible that interface system becomes easily overloaded and get complicated to comprehend at a glance. The basic paradigm of touch interface system is to design a specific display layout at a given time if some of the touch elements are selected by using tap touch, it turns into different screen layout to present a new set of options to users. If a task composed of multiple steps of tap touch to complete, we call it as workflow design. If a workflow frequently occurs in using a system, it is critical to design the series of display transitions with minimum finger traveling distance among associated finger touches. Minimizing the traveling distance will contribute to simpler system design thus make it easier to use.

The experimental task used in this study is similar to workflow with multiple steps of tap touch on different location and sizes on a display. This includes the cognitive process of identifying target, planning movement and execute movement and tapping. Task completion time in our study thus includes 1) time to identify the tap target, 2) time to plan movement, 3) time to move a finger to the target, 4) time to tap the target.

In this study, we have the following research questions to consider: 1) what are the variables affecting the performance measures defined and how much are they contributing? 2) is there a way to establish design guidelines which provide expected performance measure per design specifications without conducting performance validation experiment every time interface system implemented?

In order to simulate the real workflow usage scenario, we randomly presented tap targets with varying sizes, locations and shapes on given touch display and asked participants to tap the target quickly and accurately as possible as they can. From the detailed experimental setup, we can measure 1) time to complete a task, 2) x-y coordinate of actual tap touch according to different experimental setup and variables. From this measurement, we will consider the following measurements as our primary performance measures in this study - 1) accuracy : distance from center of target to actual touch point, 2) speed : time to complete a task, 3) angle : angle from positive x-axis to touch point, 4) speed/accuracy ratio : K constant from Chan & Childress (1990).

From accuracy measure, we will be able to identify optimal tap touch sizes with varying performance level. We will be using the following confidence internal concept using mean and standard deviation. As in Figure 3-1, $\mu \pm \sigma$ covers 68% confidence interval, $\mu \pm 2\sigma$ covers 95%, and $\mu \pm 3\sigma$ covers 99.7% with two tails on the left and right side. In our study, the only upper side is critical so we would only need one tail on the right which will give us 84%, 97.5% and 99.85% confidence coverage respectively.

Park & Han (2010) suggested minimizing error rate to achieve optimal touch target size. We will use accuracy measure to suggest optimal touch target sizes with expected performance level.

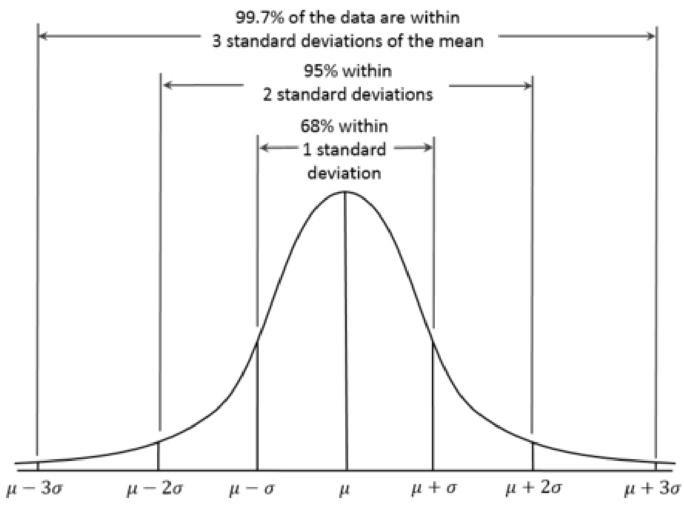

Figure 3-1 Probability distribution ranges with differing standard deviations

3.2 Methods

Tap touch is the most frequently used gesture to consist of numerous user actions in the various context of use in touch interface systems (Villamor, Willis & Wroblewski ,2010). Designers of touch interface system will benefit from better and deeper understanding of tap touch behavior, thus providing them ideal design guidelines or strategies for optimal usability systems. In order to achieve these goals, following task and experimental design were planned and executed with recruited subjects for this study. Details will be covered in the following sections.

3.2.1 Task design

The task given to all subject is to tap on a touch target presented on display. Since there are 48 different positions on a display, touch targets are presented in random order in terms of position and their sizes. We can consider this task as serial touch tasks which are similar to entering qwerty keypads or series of touch inputs to achieve specific user goals. This is also similar as serial tasks tested in experiments by Parhi & Karson (2006) which we will verify if the result of our study and theirs are confirming each other.

The input device had a 3.0-inch capacitive-type touch screen (Screen-to-Body Ratio: 51.7%, Resolution: 240×320 pixels), and its body size was 98mm×55mm×12.7mm with weight 100g. Since a form factor of mobile phones changes quickly in the market, the size variation is likely to generate certain impact on performance. But this research primarily focuses on evaluating systematic performance changes under user- and task-variability, rather than device-variability.

The task interface was programmed on Microsoft Windows Mobile 6.1 platform. After a trial run, the log files were stored and retrieved in a text file format. Time duration in milliseconds was recorded for each task from when tap target presented on display to actually tap the target. The two-dimensional coordinates for touch points were digitized in pixels with the origin at the upper-left corner bounded by the screen resolution.

3.2.2 Experimental design

Figure 3-2 shows experimental setup for tap touch tasks. There are two levels of target shapes(circle and rectangle) and three levels of target sizes(5mm, 10mm and 15mm). In terms of target position on the display, we divided x-axis by 6 segments and y-axis by 8 segments thus producing a total of 48 different positions on the display. Each position is marked by its row(1 to 8) and column number(1 to 6) in two digit number format as depicted in Figure 3-2. We used two different user postures – one handed using thumb and two-handed using index finger cradled by another hand.

The total number of experiments for a subject was 576(=2x3x48x2) which is calculated by multiplying all possible levels of the experimental setup for touch targets(=2x3=6), target positions(=6x8=48) and user postures(=2). The order of the task condition was programmed to come out in random order and logged accordingly. To mitigate fatigue and uncontrolled variability, a subject visited two different days splitting the total number of repetition into the half. The subjects were given intermittent breaks in a span of an hour (Freivalds, 2009).

The experiment was designed within-subject with a factorial design of input methods(2 levels : index finger and thumb), tap positions(48 positions) and icon sizes(3 sizes).

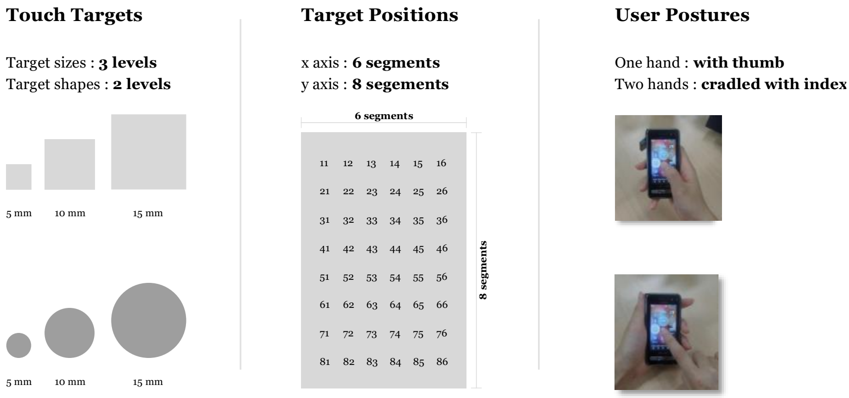

Figure 3-2 Experimental setups for tap touch tasks

3.2.3 Subjects

The study recruited 259 voluntary participants in four cities globally(New York, USA: 65, San Francisco, USA: 64, Paris, France: 67, London, UK: 59). Demographic profiles were approximately balanced in gender(males: 123, females: 136) and across age distributions(<20s: 38, 20s: 45, 30s: 36, 40s: 48, 50s: 43, >60s: 49). When participants arrived at a survey room, they were informed of the research purpose and procedure, and personal profiles were surveyed regarding their smartphone experiences. A day's participation was limited to 90 minutes, and it took two days' visit to complete an experiment. Monetary compensation was provided in return for participation. Figure 3-3 depicts the environments for survey and experiment.

Figure 3-3 Task environment

For a survey of personal profiles, individual characteristics related to performance–including handedness, the degree of familiarity with touch interaction, and habits during touch interaction–were asked. Among all participants, 12.3% were left-handed, and 15.9% had little familiarity with touch interaction.

3.2.4 Data analysis method

3.2.4.1 Analytic process

In order to answer established research questions for tap touch experiment, we investigated the 4 performance measures defined in previous section – speed(time to complete a task), accuracy(distance from center of target to actual touch point), angle(angle to touch point from positive x axis), and square root K constant from Chan & Childress (1994).

First, we have conducted Anderson-Darling normality check, Q-Q plot and histogram for all performance measures to confirm normality of the data set. Then contributing factors are identified via ANOVA analysis for all experimental variables associated, and TukeyHSD test was used to analyze the effect (Abdi & Williams, 2010). Partial eta squared was calculated to investigate the effect size of each variable to performance measures (Kirk, 1982; Tabachnick, Fidell, & Osterlind, 2001; Levine, 2002). It quantifies the effect size of a factor in a factorial experiment by a proportion of the total variability attributable to the factor (Nandy, 2012). We used boxplots to investigate overall tendency or visual patterns of each variable, along with actual data point tables with quantiles, mean and standard deviations to confirm actual amount of pattern if there is any. Finally, with all identified critical variables to performance measures, we will derive regression models to establish performance prediction models for each performance measure. Tap touch size estimation will follow after analysis of each performance measures against all affecting variables.

3.2.4.2 Data handling

A total of 146,496 data points were gathered for right handed experiments only. We assumed that any finding from right handed use could be flipped to left handed use. For task completion time, we removed data points with 300 msec or less since it is not considered as human performance could achieve. In order to handle outliers, we used interquartile range method (Faraway, 2002; Zhao, 2012). This leaves us 133,345 data points about 9% reduction from initial data points.

Initial analysis indicated that individual variability needed to be addressed to increase the reliability of established model. In order to reduce inter-subject variability, we decided to aggregate data points as a single data point for each variable and level. This way, we reduced the number of data points down to 11,043 from initial 133,345.

3.3 Results

3.3.1 Normality check

Before we move forward, we validated the normality of tap touch data for task completion time(referred as speed), distance from target center to actual tap point(referred as accuracy), angle to tap touch point from positive x-axis(referred as angle) and K coefficient from Chan & Childress (1990) equation(referred as speed accuracy ratio). Since we have a large volume of data for each measure, we cannot expect usual normality check like Anderson-Darling normality check or Q-Q plot(Figure 3-4) will confirm normality of the data due to high variability caused by high volume of data. This doesn't mean we cannot assume the normality of our data, Figure 3-5 shows probability distribution plot on the histogram of speed, accuracy and angle measures. According to the shapes of each density plot, we could assume the normality of our data set. Note these plots are aggregated from all levels of variables.

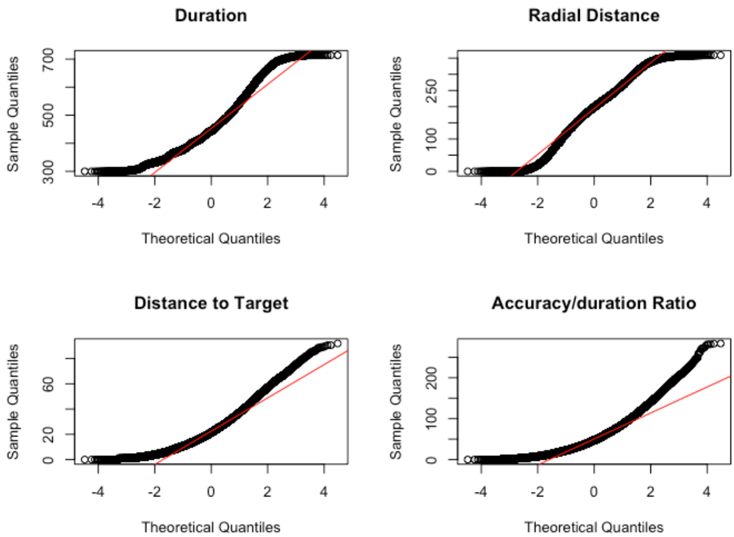

Figure 3-4 Anderson-Darling Normality Q-Q Plot for tap touch

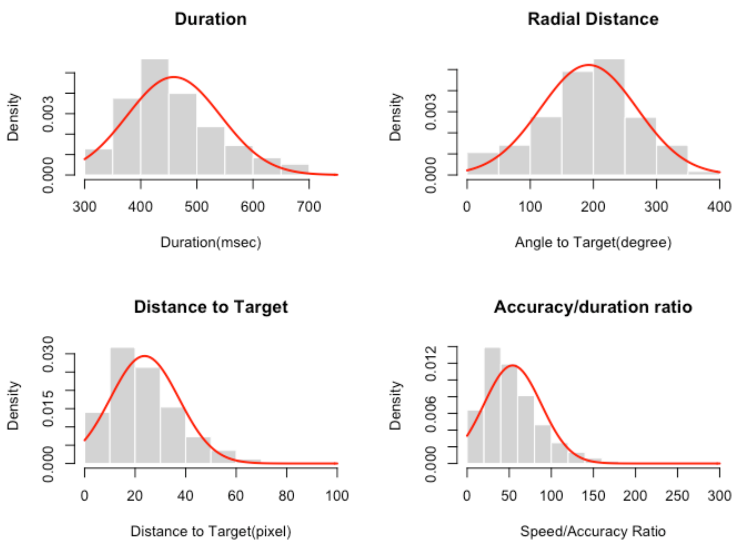

Figure 3-5 Probability distribution of speed, accuracy, angle and speed-accuracy ratio

3.3.2 Variables affecting task completion time on tap touch

Table 3-1 contains ANOVA result as well as the effect size of each variable on task completion time. We verified any data trend observed visually from Figure 3-6 and Figure 3-7 and quantile, mean and standard deviation values are presented in Table 3-2 and Table 3-3 for all levels of independent variables.

Hand posture(H), age group(A), region(R), target size(S), target X(X), and target Y(Y) statistically significant effect on task completion time for tap touch. Gender and target shape don't have an influence on task completion time.

For variables statistically significant on task completion time, TukeyHSD test was conducted to investigate detail influences for each level of the variable. For hand posture, two hands(462msec) had longer task completion time than one hand(456msec) which conforms past research around handedness. Since two handed posture involves larger muscles like forearms as well as small muscles like an index finger, it requires more energy and effort to achieve a similar level of precision compared to one-handed posture which only requires to control hand and mostly thumb muscle.

From Figure 3-6, there is a clear increasing tendency over age groups. From TukeyHSD, it indicated that 50s and 60s are not different statistically(Refer to Table 3-2 and Table 3-3 for detailed numbers for each variable level). This also confirms our common sense that younger people will make faster movement under the same task condition.

Regional impact is also observed, but when we checked TukeyHSD result, only New York showed the highest value while other regions don't show a significant difference.

Target size also shows clear increasing tendency as target size becomes smaller which means smaller targets requires more attention and thus more time to complete the task. This can be explained with OIIM model proposed by Meyer et. al (1988) that final adjustment movement close to target will be more difficult to complete if the target size becomes smaller thus requires more time. The actual time difference can be seen on Table 3-3.

It is expected that location of the target object has an influence on task completion time and we had the same result. From Figure 3-7 we can observe that task completion time increases as target positions become closer to the edge of the screen for both X and Y axis thus boxplot shows parabolic shape where minimal point appears towards the center. This might partly because of task condition is not fully controlled where to reside finger after each tap. Meaning, after the first tap, participants were not asked to leave their fingers on the target until they are presented next target. Thus, we can assume that they may reside their finger close to the center of the screen in order to minimize the travel distance to the next target. From TukeHSD test, it appeared that task completion time on 140 and 180 on Y axis showed the lowest value, while point 140 on X axis showed the minimum which is slightly skewed toward the right. This may be we used experimental data for right-hand usage only which may help right-handed participants reach the target close to right faster than elsewhere.

Table 3-1 ANOVA and effect size(partial eta squared) for task completion time for tap touch

	η_p^2	Sum Sq	Df	F value	Pr(>F)
Hand(H)	0.016	248862	1	187.402	< 2e-16***
Age group(A)	0.247	4801256	4	903.878	< 2e-16***
Region(R)	0.023	355184	3	89.155	< 2e-16***
Gender(G)	0.000	1170	1	0.880	0.3480
Target size(S)	0.091	1469032	2	553.114	< 2e-16***
Target shape(P)	0.000	891	1	0.671	0.4127
Target X(X)	0.155	2682008	5	403.929	< 2e-16***
Target Y(Y)	0.199	3643766	7	391.983	< 2e-16***
Residuals		14631451	11018		

*** P-value < 0.001, ** P-value < 0.01, * P-value < 0.05

Table 3-2 Quantile, mean and standard deviation of task completion time(msec) of demography and interaction related variables for tap touch

Variables	Levels	Quantile					Mean(SD)
		0%	**25%**	**50%**	**75%**	**100%**	
Hand	One	300	396	442	504	714	456(83)
	Two	300	403	447	508	714	462(83)
Age group	20s	300	376	416	469	714	432(76)
	30s	300	387	432	483	714	443(77)
	40s	300	404	446	496	714	456(76)
	50s	300	416	468	532	714	481(85)
	60s	300	416	470	549	714	487(91)
Region	London	300	402	445	503	714	459(81)
	Paris	300	397	444	507	714	459(86)
	NY	300	403	447	510	714	462(83)
	SF	300	397	441	504	714	456(83)
Gender	Male	300	401	444	507	714	459(83)
	Female	300	400	445	506	714	459(83)

Table 3-3 Quantile, mean and standard deviation of task completion time(msec) of design-related variables for tap touch.

Variables	Levels	Quantile					Mean(SD)
		0%	**25%**	**50%**	**75%**	**100 %**	
Target size (pixel)	36	300	433	483	550	714	494(86)
	70	300	398	440	492	714	451(78)
	106	300	385	427	483	714	442(78)
Target shapes	Circle	300	400	444	506	714	458(83)
	Rectangle	300	400	445	507	714	459(83)
Target X (pixel)	20	302	464	513	578	714	523(81)
	60	300	414	457	513	714	470(78)
	100	300	395	438	491	714	450(79)
	140	300	381	426	484	714	442(81)
	180	300	390	436	494	714	451(83)
	220	300	448	507	580	714	516(87)
Target Y (pixel)	20	302	465	515	580	714	524(80)
	60	300	413	457	515	714	471(79)
	100	300	396	438	489	714	451(80)
	140	300	381	422	481	714	439(79)
	180	300	380	424	483	714	441(81)
	220	300	395	439	494	714	452(81)
	260	300	412	458	518	714	471(81)
	300	300	475	525	590	714	533(80)

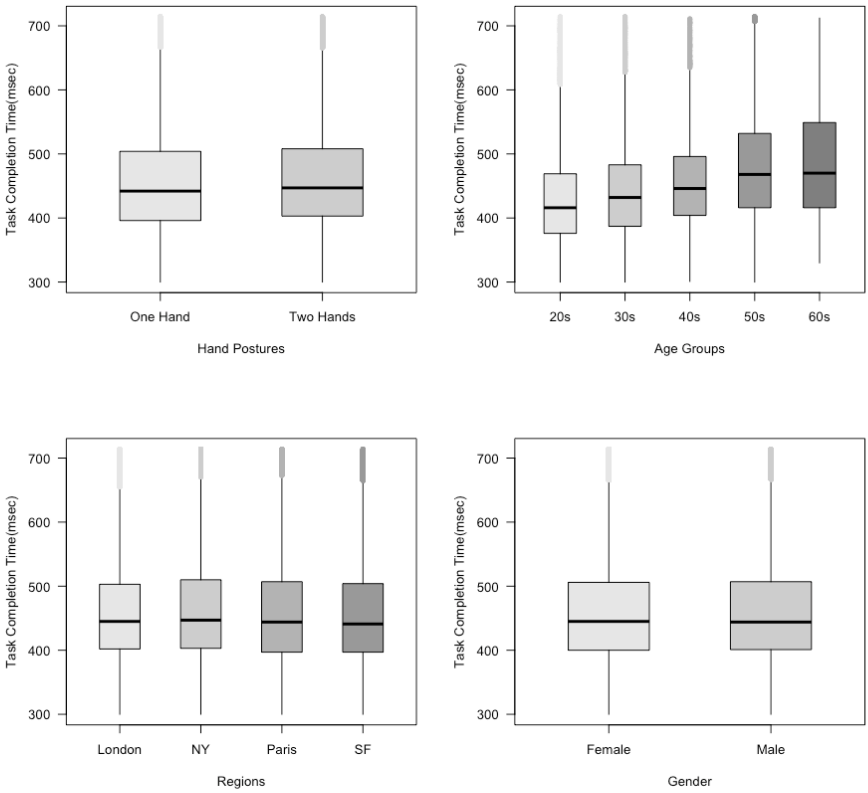

Figure 3-6 Boxplots of demography and interaction related variables regarding task completion time for tap touch

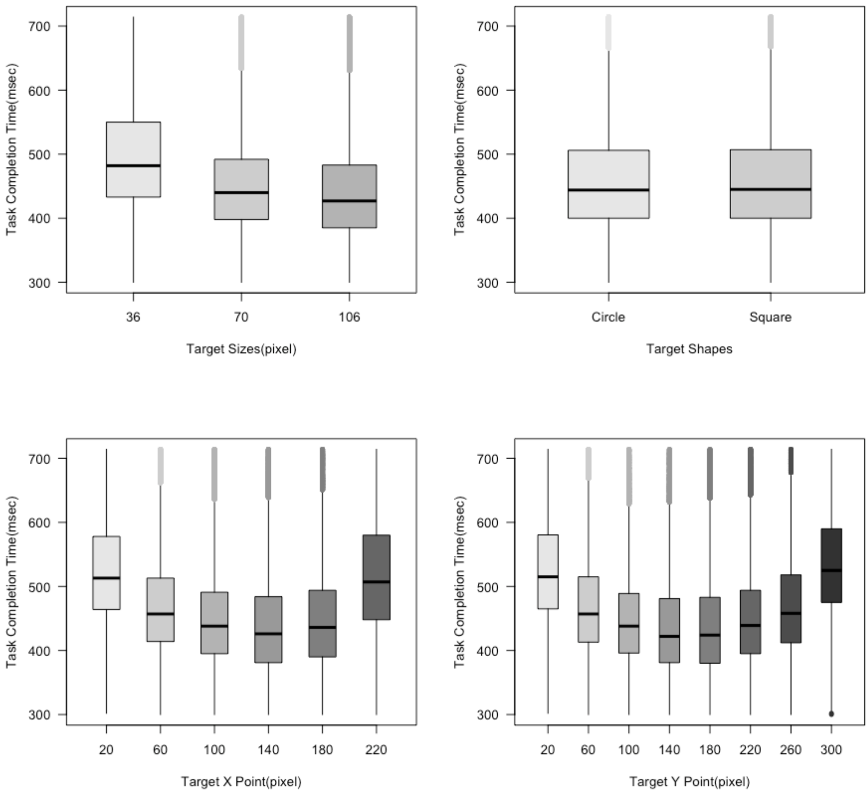

Figure 3-7 Boxplots of design-related variables regarding task completion time for tap touch

Investigating effect size of each variable for task completion time will allow us to identify how much of contribution of each variable affecting the performance. We can also investigate relative contribution amount by calculating the ratio of effect size. By order of percent contribution, age group(33.8%) showed the most value followed by target Y(27.2%), target X(21.2%), target size(12.4%), region(3.3%), hand(2.2%), gender(0%) and target shape(0%). This matches with the ANOVA and TukeyHSD result in that contributing factors are identified as statistically significant. However, region and hand variables have effect size negligible to task completion time. Thus, we will use age group, target X, target Y and target size to build a prediction model for task completion time. Table 3-4 includes estimated coefficients from linear regression. We have added square terms for target X and target Y since we observed parabolic shape for those variables.

Table 3-4 Prediction model of task completion time for tap touch

	Estimated	Std Error	t-value	Pr(>|t|)
(Intercept)	5.531e+02	2.224e+00	248.636	< 2e-16***
S	-4.437e-01	1.334e-02	-33.250	< 2e-16***
X	-1.258e+00	2.792e-02	-45.063	< 2e-16***
X^2	4.872e-03	1.136e-04	42.883	< 2e-16***
Y	-9.769e-01	1.936e-02	-50.468	< 2e-16***
Y^2	3.126e-03	5.897e-05	53.004	< 2e-16***
A	1.687e+00	2.850e-02	59.184	< 2e-16***
Residual standard error: 37.51 on 11036 degrees of freedom				
Multiple R-squared: 0.5305, Adjusted R-squared: **0.5303**				
F-statistic: 2078 on 6 and 11036 DF, p-value: < 2.2e-16				

*** P-value < 0.001, ** P-value < 0.01, * P-value < 0.05

3.3.3 Variables affecting distance to target on tap touch

Table 3-5 contains ANOVA result as well as the effect size of each variable on the distance to the target. We verified any data trend observed visually from Figure 3-8 and Figure 3-9 and quantile, mean and standard deviation values are presented in Table 3-6 and Table 3-7 for all levels of independent variables. It turned out all variables have statistically significant effect on the distance to target for tap touch. TukeyHSD test was conducted to investigate detail influences for each level of the variable.

For hand posture, two hands(21.43 pixels) had a shorter distance to target than one hand(26.07 pixels). This means one hand posture yield less accurate performance than two hands posture. This confirms the findings from Wang and Ren (2009) that precision of index finger is slightly better than a thumb. This can also be explained with speed-accuracy trade off. From the previous section, we know task completion time for one hand posture is faster than two hands posture where the distance to target indicated otherwise. Speed trade-off explains a situation where accuracy is sacrificed over speed which we are observing in this case. One hand posture showed faster task completion time and less accurate result.

For age group, we don’t see increasing tendency as clear as task completion time, only slightly observed – youngest group showed the least accurate result compared to other age groups. Regional impact is also minimal and negligible.

The female participants generally showed less accurate result than the male group which could also be explained as speed-accuracy trade off. From previous researches (Denckla, 1973, 1974;Baken, 1986; Lomas, 1980; Lomas & Kimura, 1976; Tiffin & Asher, 1948), the female tends to demonstrate better performance over male, thus we could assume that accuracy might be sacrificed for female which matches with our observation here. Female(24.41 pixels) group is less accurate than male group(22.96 pixels) on the average.

For target size, we don't observe any increasing or decreasing tendency. Target shapes also didn't show any significant differences though it is statistically significant on the distance to the target. For target X and target Y, there is a slight decreasing tendency towards the bottom right corner of the screen thus more accurate(Figure 3-9).

Table 3-5 ANOVA and effect size(partial eta squared) for distance to target for tap touch

	η_p^2	Sum Sq	Df	F value	Pr(>F)
Hand(H)	0.140	64994	1	1804.219	< 2e-16***
Age group(A)	0.011	4551	4	31.584	< 2e-16***
Region(R)	0.006	2580	3	23.878	< 2e-16***
Gender(G)	0.011	4500	1	124.907	< 2e-16***
Target size(S)	0.028	11778	2	163.470	< 2e-16***
Target shape(P)	0.001	711	1	19.742	< 2e-16***
Target X(X)	0.139	63999	5	355.319	< 2e-16***
Target Y(Y)	0.094	41474	7	164.471	< 2e-16***
Residuals		396907	11018		

*** P-value < 0.001, ** P-value < 0.01, * P-value < 0.05

Table 3-6 Quantile, mean and standard deviation of distance to target center(pixel) of demography and interaction related variables for tap touch

Variables	Levels	Quantile					Mean(SD)
		0%	**25%**	**50%**	**75%**	**100%**	
Hand	One	0	15.2	24.0	34.6	91.9	26.0(14.3)
	Two	0	12.3	19.2	28.2	90.5	21.4(12.3)
Age group	20s	0	14.3	22.8	33.1	90.5	24.9(14.0)
	30s	0	13.4	21.1	31.2	91.9	23.4(13.4)
	40s	0	13.6	20.8	29.8	85.2	22.8(12.6)
	50s	0	13.4	21.1	31.0	89.2	23.4(13.4)
	60s	0	13.6	21.9	30.0	81.6	23.1(12.8)
Region	London	0	13.3	21.0	30.5	88.3	23.1(13.2)
	Paris	0	13.4	21.2	31.4	91.9	23.7(13.6)
	NY	0	13.6	21.2	31.3	89.1	23.7(13.6)
	SF	0	14.2	22.2	32.3	90.5	24.5(13.7)
Gender	Male	0	13.0	20.6	30.4	91.9	22.9(13.2)
	Female	0	14.1	22.0	32.2	90.5	24.4(13.8)

Table 3-7 Quantile, mean and standard deviation of distance to target center(pixel) of design-related variables for tap touch

Variables	Levels	Quantile					Mean(SD)
		0%	**25%**	**50%**	**75%**	**100%**	
Target size (pixel)	36	0	13.4	20.5	31.0	91.9	23.3(13.4)
	70	0	13.0	20.5	30.0	90.5	22.6(13.0)
	106	0	14.3	22.6	32.7	89.9	24.6(13.9)
Target shapes	Circle	0	13.4	21.1	31.0	90.5	23.4(13.3)
	Rectangle	0	13.8	21.8	31.9	91.9	24.0(13.7)
Target X (pixel)	20	0	17.0	27.6	38.1	90.5	29.0(15.2)
	60	0	15.6	24.3	34.6	90.5	26.3(14.2)
	100	0	14.1	21.4	30.5	89.8	23.4(12.7)
	140	0	12.3	19.4	28.6	88.4	21.8(12.7)
	180	0	12.6	20.5	31.0	89.1	23.0(13.6)
	220	0	12.0	16.2	25.2	91.9	20.0(11.4)
Target Y (pixel)	20	1	16.1	26.2	37.6	91.9	28.3(15.4)
	60	0	14.8	24.3	35.5	90.5	26.3(15.0)
	100	0	14.1	21.9	31.7	89.1	24.0(13.4)
	140	0	13.4	20.2	29.8	89.1	22.7(12.7)
	180	0	13.4	20.5	29.5	84.8	22.5(12.5)
	220	0	12.7	19.8	29.0	90.5	22.0(12.7)
	260	0	13.1	21.9	31.7	84.8	23.7(13.7)
	300	0	13.6	19.4	31.0	82.7	23.4(13.2)

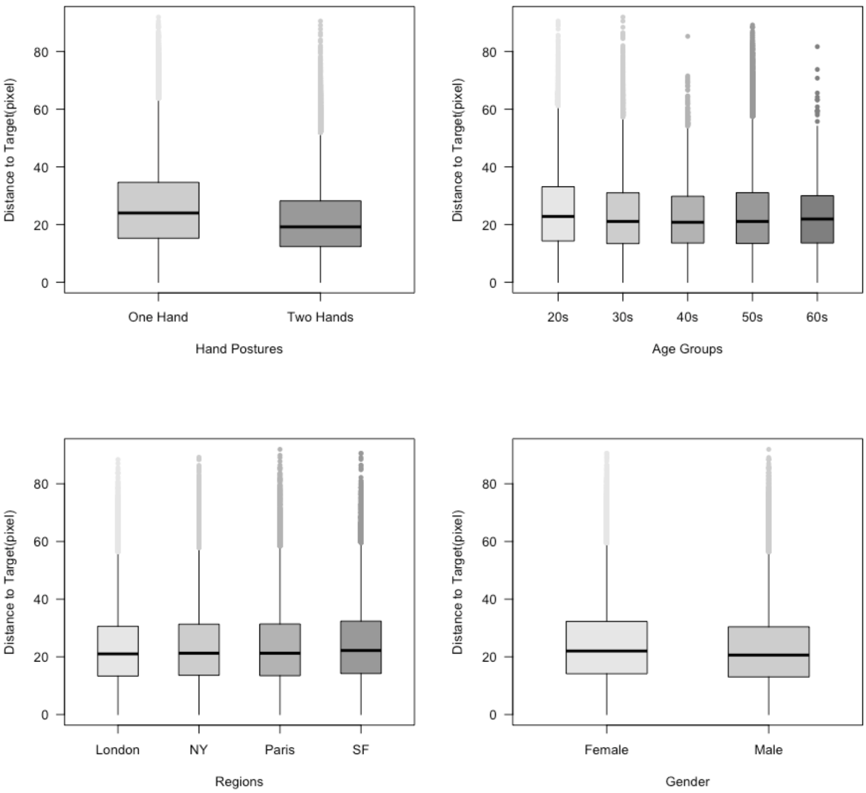

Figure 3-8 Boxplots of demography and interaction related variables regarding distance to target for tap touch

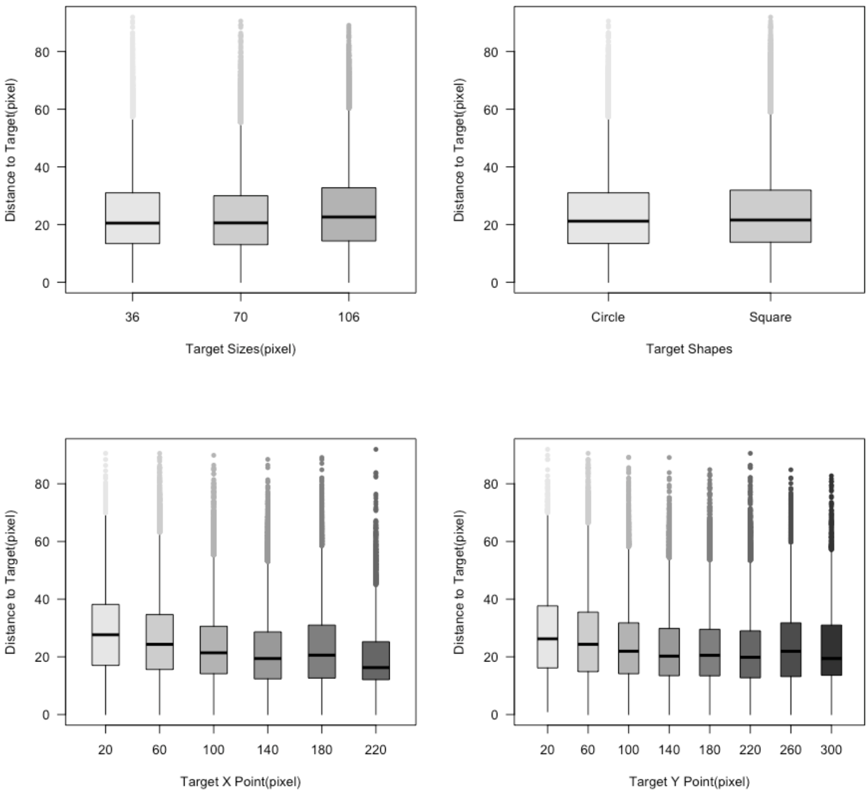

Figure 3-9 Boxplots of design-related variables regarding the distance to target for tap touch

Investigating effect size of each variable for distance to target will allow us to identify how much of contribution of each variable affecting the performance. We can also investigate relative contribution amount by calculating the ratio of effect size. By order of percent contribution, hand(32.6%) showed the most value followed by target X(32.3%), target Y(21.9%), target size(6.5%), age group(2.6%), gender(2.6%), region(1.4%) and target shape(0.2%). Even though ANOVA and TukeyHSD indicated that all variables are statistically significant on the distance to target measure, percent effect size indicates that only target X, target Y and hand cover more than 80% of contribution. Thus we decided to use only those three variables for prediction modeling. Table 3-8 includes estimated coefficients from linear regression. In this model, H is a categorical variable thus used as dummy variable lockeiled on Two hands level by default. Thus, if that variable is set to 1, then the coefficient explains the difference between two hands and one hand.

Table 3-8 Prediction model of distance to target for tap touch

	Estimated	Std Error	t-value	Pr(>|t|)
(Intercept)	32.686	0.196	166.58	< 2e-16***
X	-0.035	0.001	-33.17	< 2e-16***
Y	-0.016	0.000	-21.86	< 2e-16***
H: Two hands	-4.860	0.122	-39.74	< 2e-16***
Residual standard error: 6.426 on 11039 degrees of freedom				
Multiple R-squared: 0.2223, Adjusted R-squared: **0.2221**				
F-statistic: 1052 on 3 and 11039 DF, p-value: < 2.2e-16				

*** P-value < 0.001, ** P-value < 0.01, * P-value < 0.05

3.3.4 Variables affecting angle from positive x-axis to touch point on tap touch

Table 3-9 contains ANOVA result as well as the effect size of each variable on the angle from positive x-axis to touch point. We verified any data trend observed visually from Figure 3-10 and Figure 3-11 and quantile, mean and standard deviation values are presented in Table 3-10 and Table 3-11 for all levels of independent variables. Hand, age group, gender, target size, target X and target Y are statistically significant variables for the angle from the positive x-axis. TukeyHSD test was conducted to investigate detail influences for each level of the variable. For hand posture, both levels fall into quadrant III on the average. Age group, gender, target size, target X and target Y are variables statistically significant though not demonstrating any clear tendency.

Table 3-9 ANOVA and effect size(partial eta squared) for angle to target for tap touch

	η_p^2	Sum Sq	Df	F value	Pr(>F)
Hand(H)	0.019	247449	1	214.1577	< 2e-16***
Age group(A)	0.022	290448	4	62.8427	< 2e-16***
Region(R)	0.000	7692	3	2.2189	0.08374
Gender(G)	0.000	4805	1	4.1589	0.04144*
Target size(S)	0.006	77612	2	33.5850	< 2e-16***
Target shape(P)	0.000	2232	1	1.9316	0.16461
Target X(X)	0.004	51368	5	8.8914	< 2e-16***
Target Y(Y)	0.194	3060798	7	378.4286	< 2e-16***
Residuals		12730793	11018		

*** P-value < 0.001, ** P-value < 0.01, * P-value < 0.05

Table 3-10 Quantile, mean and standard deviation of angle from positive x-axis to touch point(degree) of demography and interaction related variables for tap touch

Variables	Levels	Quantile					Mean(SD)
		0%	**25%**	**50%**	**75%**	**100%**	
Hand	One	0	154.4	203.1	244.7	358.9	196.9(75.7)
	Two	0	139.2	193.5	238.4	359.0	188.3(76.9)
Age group	20s	0	149.5	203.6	247.0	358.9	196.0(76.9)
	30s	0	143.1	198.4	243.4	359.0	192.2(78.1)
	40s	0	165.9	212.4	247.8	358.2	202.9(72.9)
	50s	0	146.3	195.5	237.2	358.9	190.4(75.1)
	60s	0	135.0	210.9	265.3	356.4	198.6(89.0)
Region	London	0	143.1	196.6	240.2	358.9	190.9(76.4)
	Paris	0	146.3	200.9	246.2	358.9	194.0(78.1)
	NY	0	150.7	198.4	238.3	358.7	192.8(72.6)
	SF	0	147.0	198.9	243.3	359.0	192.5(78.6)
Gender	Male	0	143.9	196.2	242.1	358.9	191.4(77.1)
	Female	0	149.0	200.7	241.6	359.0	193.6(75.8)

Table 3-11 Quantile, mean and standard deviation of the angle from positive x-axis to touch point(degree) of design-related variables for tap touch

Variables	Levels	Quantile					Mean(SD)
		0 %	**25%**	**50%**	**75%**	**100 %**	
Target size (pixel)	36	0	154.3	202.3	242.3	358.9	196.5(73.4)
	70	0	147.9	198.4	241.1	358.6	192.7(75.5)
	106	0	140.8	196.3	241.9	359.0	190.1(78.7)
Target shapes	Circle	0	146.3	198.4	240.6	359.0	192.0(75.7)
	Rectangle	0	146.6	199.6	243.4	358.9	193.1(77.1)
Target X (pixel)	20	0	161.5	194.0	223.1	355.6	192.6(66.3)
	60	0	158.5	195.4	225.0	358.9	191.2(60.2)
	100	0	153.4	199.4	236.3	358.3	193.4(67.8)
	140	0	136.3	203.0	255.9	358.2	194.0(82.9)
	180	0	122.0	199.4	259.6	359.0	191.0(90.9)
	220	0	130.2	214.9	252.6	358.9	196.8(86.2)
Target Y (pixel)	20	1	167.3	226.2	256.3	358.2	211.7(69.9)
	60	0	180.0	222.0	255.9	358.9	213.3(68.8)
	100	0	175.0	214.6	251.5	358.8	208.5(69.9)
	140	0	154.0	201.0	243.4	359.0	195.7(74.9)
	180	0	142.5	195.9	240.2	358.9	191.0(78.4)
	220	0	135.0	189.4	230.5	358.9	184.1(79.1)
	260	0	111.0	158.1	201.8	358.9	161.0(75.7)
	300	0	124.9	189.4	225.0	357.3	181.1(75.8)

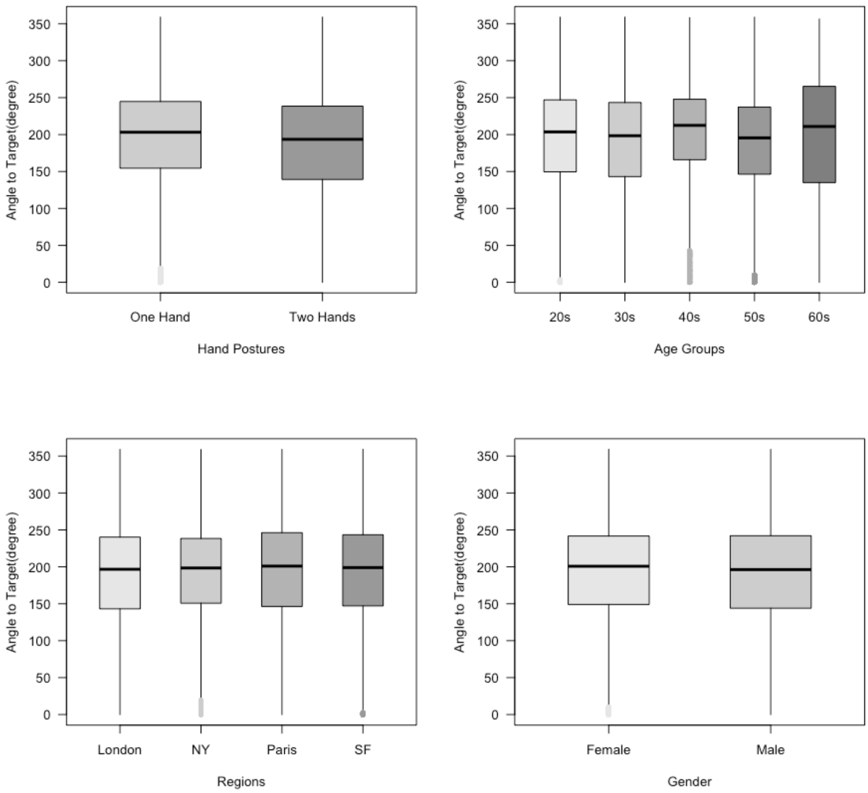

Figure 3-10 Boxplots of demography and interaction related variables regarding angle to target for tap touch

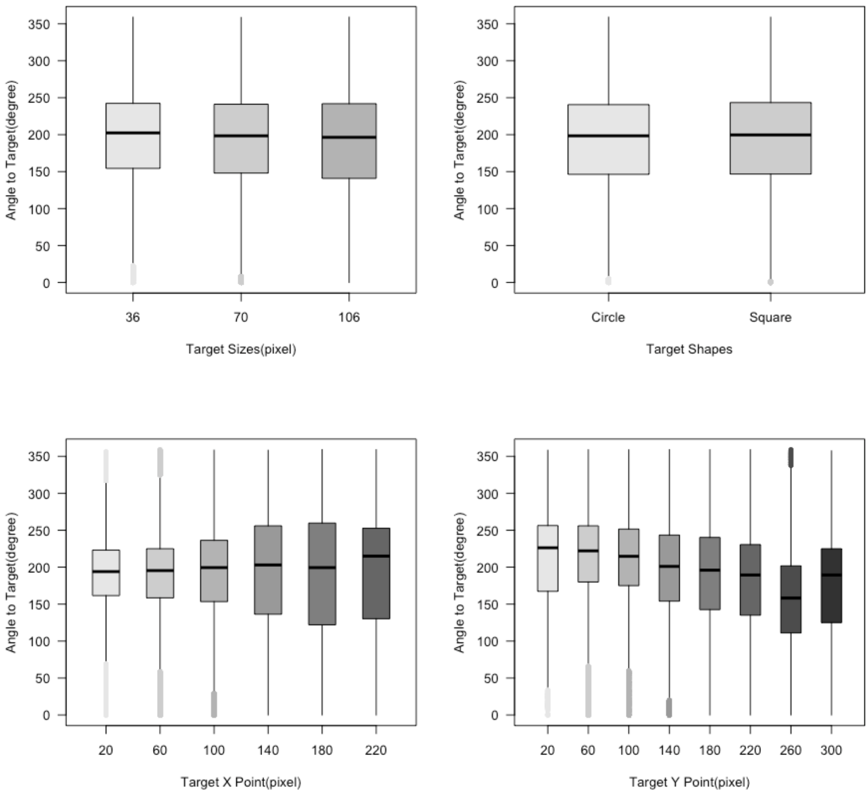

Figure 3-11 Boxplots of design-related variables regarding angle to target for tap touch

Investigating effect size of each variable for an angle to target will allow us to identify how much of contribution of each variable affecting the performance. We can also investigate relative contribution amount by calculating the ratio of effect size. By order of percent contribution, target Y(79.2%) showed the most value followed by age group(9%), hand(7.8%), target size(2.4%), target

X(1.6%) and region, gender, target shape have 0% contribution. It is interesting to note that target Y contributes more than 70% of angle, which may mean angular distance from x-axis only depends on Y positions. Table 3-12 includes estimated coefficients from linear regression. In this model, H is a categorical variable thus used as dummy variable locked on Two hands level by default. Thus, if that variable is set to 1, then the coefficient explains the difference between two hands and one hand.

Table 3-12 Prediction model of angle to target for tap touch

	Estimated	Std Error	t-value	Pr(>|t|)
(Intercept)	236.297	1.247	189.424	< 2e-16***
Y	-0.191	0.004	-46.263	< 2e-16***
A	-0.122	0.026	-4.555	5.3e-06***
H: Two hands	-9.541	0.667	-14.295	< 2e-16***
Residual standard error: 35.07 on 11039 degrees of freedom				
Multiple R-squared: 0.1764, Adjusted R-squared: 0.1762				
F-statistic: 788 on 3 and 11039 DF, p-value: < 2.2e-16				

*** P-value < 0.001, ** P-value < 0.01, * P-value < 0.05

3.3.5 Variables affecting speed accuracy ratio on tap touch

We calculated K constant from equation 2-3 (Chan & Childress, 1990) assuming variance of noise as distance to touch target center and speed of movement being task completion time eventually contribute to explain speed accuracy ratio of the task. Thus, if this value becomes large, the behavioral strategy is focusing on faster movement than the accurate result. If it becomes small, focus shifts on more accurate movement than faster movement.

Table 3-13 contains ANOVA result as well as the effect size of each variable on speed accuracy ratio. We verified any data trend observed visually from Figure 3-12 and Figure 3-13 and quantile, mean and standard deviation values are presented in Table 3-14 and Table 3-15 for all levels of independent variables. It turned out all variables have statistically significant effect on speed accuracy ratio for tap touch. TukeyHSD test was conducted to investigate detail influences for each level of the variable.

For hand posture, two hands(48.70) had a smaller value than one hand(59.41) thus we can conclude that one hand posture generally tends to focus on speed rather than accuracy. A similar trend is observed on age group since it shows decreasing value as age group becomes older, which means younger generation tend to prioritize on speed while the older group on accuracy with the sacrifice of speed. Regional difference is not clear. For gender, female shows larger value of 55.44 than the male group with 52.42. This also confirms previous findings that female showed faster performance over the male group. As target size grows, this ratio value becomes larger. Thus, speed becomes more of focus than accuracy as target size grows. For target shape, target X and target Y, we don't observe any clear tendency as other variables though they are significant variables.

Table 3-13 ANOVA and effect size(partial eta squared) for speed accuracy ratio for tap touch

	η_p^2	Sum Sq	Df	F value	Pr(>F)
Hand(H)	0.134	358981	1	1708.741	< 2e-16***
Age group(A)	0.050	122792	4	146.122	< 2e-16***
Region(R)	0.011	27613	3	43.813	< 2e-16***
Gender(G)	0.007	16632	1	79.170	< 2e-16***
Target size(S)	0.059	144514	2	343.942	< 2e-16***
Target shape(P)	0.001	3302	1	15.718	< 2e-16***
Target X(X)	0.077	193368	5	184.086	< 2e-16***
Target Y(Y)	0.046	111529	7	75.839	< 2e-16***
Residuals		2314715	11018		

*** P-value < 0.001, ** P-value < 0.01, * P-value < 0.05

Table 3-14 Quantile, mean and standard deviation of speed/accuracy ratio of demography and interaction related variables for tap touch

Variables	Levels	Quantile					Mean(SD)
		0%	**25%**	**50%**	**75%**	**100%**	
Hand	One	0	32.8	53.0	78.7	283.3	59.4(35.5)
	Two	0	25.8	41.9	64.1	283.7	48.7(31.4)
Age group	20s	0	32.5	53.2	79.7	283.7	60.4(37.5)
	30s	0	29.5	47.9	72.7	281.6	54.9(34.4)
	40s	0	28.8	45.5	68.6	283.3	51.9(31.4)
	50s	0	27.1	44.5	67.7	281.6	50.8(31.7)
	60s	0	27.0	44.1	64.7	167.3	49.5(30.1)
Region	London	0	28.1	46.1	70.0	280.9	52.6(33.0)
	Paris	0	28.6	47.1	71.9	283.3	53.9(34.0)
	NY	0	28.7	46.7	71.0	271.6	53.6(33.6)
	SF	0	30.2	49.2	74.3	283.7	56.3(35.2)
Gender	Male	0	27.7	45.4	69.6	283.7	52.4(33.5)
	Female	0	29.9	48.8	73.5	283.3	55.4(34.2)

Table 3-15 Quantile, mean and standard deviation of speed/accuracy ratio of design-related variables for tap touch

Variables	Levels	Quantile					Mean(SD)
		0%	**25%**	**50%**	**75%**	**100%**	
Target size (pixel)	36	0	26.4	42.0	65.1	281.6	49.2(31.0)
	70	0	28.2	45.9	69.3	283.3	52.2(32.7)
	106	0	31.5	51.6	77.4	283.7	58.2(35.9)
Target shapes	Circle	0	28.6	46.7	70.8	283.7	53.3(33.5)
	Rectangle	0	29.1	47.7	72.6	280.9	54.7(34.4)
Target X (pixel)	20	0	31.8	52.4	76.8	276.9	57.7(33.6)
	60	0	32.2	52.3	77.4	283.7	58.6(35.7)
	100	0	30.3	48.1	71.8	283.3	54.5(33.3)
	140	0	27.3	44.7	68.2	281.6	51.4(32.8)
	180	0	27.5	46.3	71.1	280.9	53.2(34.2)
	220	0	23.2	32.2	50.7	248.1	40.5(26.5)
Target Y (pixel)	20	1.4	30.0	50.4	75.1	219.0	56.1(33.2)
	60	0	30.4	51.7	78.8	283.3	58.4(36.6)
	100	0	30.4	49.1	73.5	283.7	55.8(34.3)
	140	0	30.0	47.2	70.7	269.2	53.8(32.8)
	180	0	29.5	46.6	70.3	271.2	53.4(32.8)
	220	0	27.1	44.1	67.0	281.6	51.1(33.0)
	260	0	27.2	46.3	71.0	280.9	52.9(34.4)
	300	0	25.0	36.8	60.0	213.4	45.5(28.5)

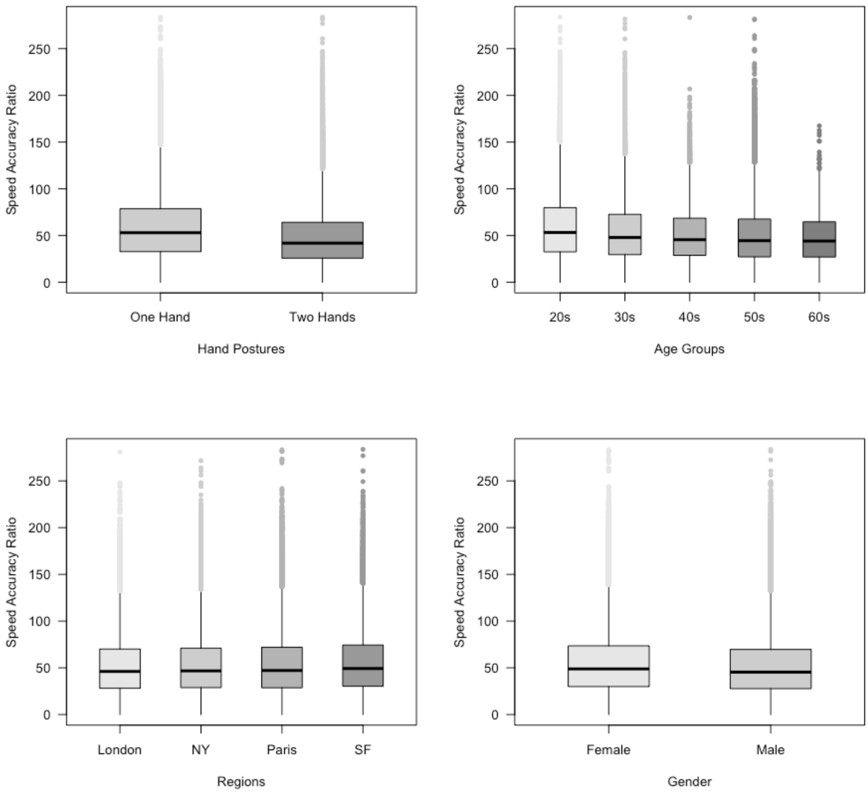

Figure 3-12 Boxplots of demography and interaction related variables regarding speed/accuracy ratio for tap touch

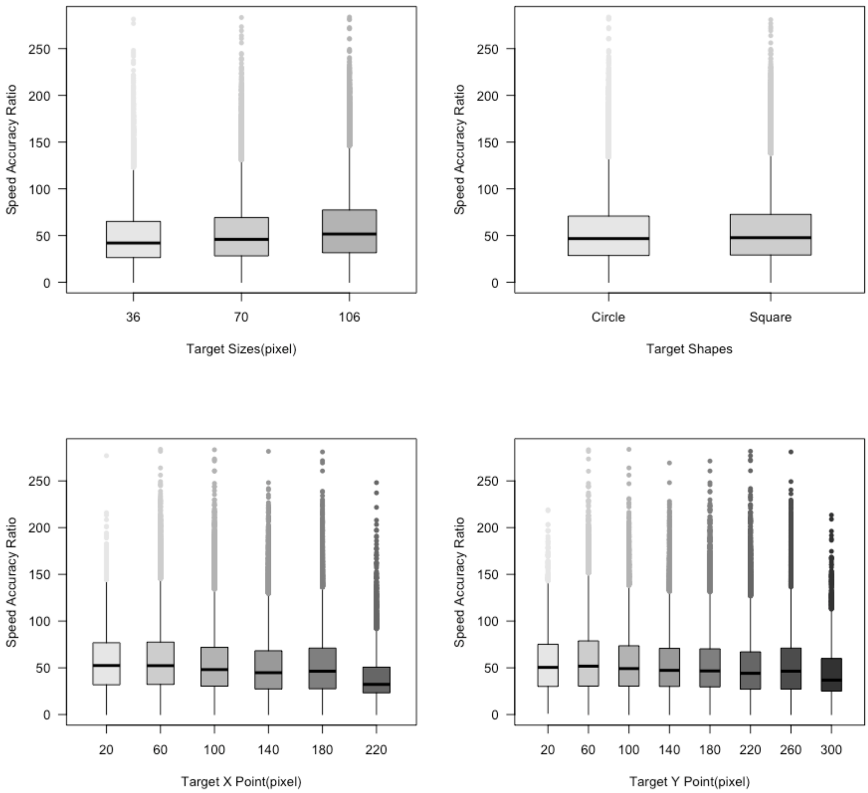

Figure 3-13 Boxplots of design-related variables regarding speed/accuracy ratio for tap touch

Investigating effect size of each variable for speed accuracy ratio will allow us to identify how much of contribution of each variable affecting the performance. We can also investigate relative contribution amount by calculating the ratio of effect size. By order of percent contribution, hand(34.8%) showed the most value followed by age target X(20.0%), target size(15.3%), age group(13%), target Y(11.9%), region(2.9%), gender(1.8%) and target shape have 0.3%

contribution. From this finding, we decided to include top 5 variables to build prediction model. Table 3-16 includes estimated coefficients from linear regression. In this model, H is a categorical variable thus used as dummy variable locked on Two hands level by default. Thus, if that variable is set to 1, then the coefficient explains the difference between two hands and one hand.

Table 3-16 Prediction model of speed accuracy ratio for tap touch

	Estimated	Std Error	t-value	Pr(>|t|)
(Intercept)	72.420	0.675	107.18	< 2e-16***
S	0.130	0.004	26.71	< 2e-16***
X	-0.063	0.002	-25.93	< 2e-16***
Y	-0.036	0.001	-20.79	< 2e-16***
A	-0.259	0.011	-22.75	< 2e-16***
H: Two hands	-11.429	0.283	-40.37	< 2e-16***
Residual standard error: 14.88 on 11037 degrees of freedom				
Multiple R-squared: 0.2623, Adjusted R-squared: **0.262**				
F-statistic: 785 on 5 and 11037 DF, p-value: < 2.2e-16				

*** P-value < 0.001, ** P-value < 0.01, * P-value < 0.05

3.4 Conclusion and discussion

3.4.1 Speed accuracy trade off

We have investigated 4 performance measures across 8 independent variables. Among these performance measures, we have identified speed accuracy trade off from task completion time, distance to target center(a measure of accuracy - smaller value represents more accurate result), and speed accuracy ratio. Except for the regional effect, hand, gender, age group demonstrated speed-accuracy trade off. Technically, we were not able to calculate speed (velocity) due to lack of actual travel distance between taps, we have used task completion time as a measure of speed.

For task completion time, one hand posture showed faster movement than two handed posture which could be explained by different types of muscles were involved in completing the task. The accuracy of one hand posture showed lower than two handed posture thus we observed speed accuracy trade off on hand posture variable. Speed accuracy ratio is useful when we want to take into account both aspect as a single measure of performance instead of two. In our case, larger ratio value represents speed focused strategy and accuracy focused strategy for smaller ratio value.

Age and gender related trade-offs were also observed. Older group showed slower completion time while more accurate result compared to the younger group. Female showed faster result than male and less accurate than male.

Speed accuracy trade off was also observed for target size variable. As target size grows bigger, they tend to focus more on the speed than the accuracy and vice versa. This could partly because of cognitive pressure incurred by smaller tap target making them more cautious to hit the target correctly while larger target imposed lesser pressure on them. Considering this, it seems better to provide larger tap target in all cases if we can assume speed accuracy trade-off exists.

However, in the smaller mobile display, making all touch elements larger makes us confront another trade-off situation – information density and usability. For example, if we put 3 large touch elements on a single display, they will be much easier to tap compared to putting 10 screen elements on the same screen area. However, exposing 10 screen elements potentially provides more options to choose at a given time, thus make it less navigation heavy compared to fewer screen element design strategy. To find the golden balanced ratio between information density and usability could be another research topic. From our research result, leveraging performance prediction model to estimate expected performance of given design paradigm could help mitigate the trade-off situation mentioned above.

For target locations, task completion time was observed to decrease towards the center of the display while accuracy and speed accuracy ratio showed decreasing trend from top to bottom for Y axis and left to right for the X axis. We have discussed that speed may present the best performance towards the center of the screen due to lack of control of the experiment thus most of the participants may stand by close to center of the screen while waiting for next tap target instead of leaving their fingers on the previous tap target. Even though it requires further investigation to make sure this premise is correct or not, it may be convincing usage scenario especially when we imagine how we use our mobile device. We don't leave our fingers on the screen to wait for the next prompt, rather hovering over on screen ready to hit the target. Thus, the observed pattern could be considered as one of design strategy if there is any screen element requires frequent access and should not be miss hit, it seems obvious putting them towards the center of the screen may help to increase the usability.

For accuracy measure, it becomes more accurate towards the bottom right corner of the screen. This may be due to the fact that we have observed only right handed use cases. Speed accuracy ratio also showed a similar trend which means they tend to focus on accuracy towards the bottom right corner, on speed towards the top left corner of the screen. There is no clear explanation on this, but it is an interesting observation. In general, we tend to consider top left corner zone is golden spot to achieve more attention thus putting more critical screen elements towards that area. However, putting interactive elements on the top left corner may not be a good design decision since it hinders to display information, and less accurate area according to our finding. Android's FAB(floating action button) design may be a good example of leveraging this finding – putting a frequently used interactive button on bottom right corner.

3.4.2 Implications on angle from X axis

We have investigated angle from positive X axis to understand if there is any tendency or skewness observed around the center of the target. On the average, we found that people tend to tap on quadrant III. However distribution of the angle data covers on all quadrants if we look at boxplots(Figure 3-10 and Figure 3-11) and data tables(Table 3-10 and Table 3-11). There is no clear tendency – either increasing, decreasing or parabolic - observed for variables statistically significant on an angle such as hand, age group, gender, target size, target X and target Y.

If we look at the data at a macro level, the total mean of angle is 196.63 degree and the standard deviation is 38.64 degree. We know that assuming a normal distribution, $\mu \pm 2\sigma$ covers 95% of probability space(Figure 3-1). That range is from 119.35 degrees to 273.91 degrees which mostly on quadrant II and III which is depicted as pink area in the following Figure 3-14. Considering only right handed data points were used for analysis, the opposite may be true for left handed data points which may cover quadrant I and IV. This finding can be leveraged when designing actual touch area calibration, not visual touch area. For right handed users, if actual touch area is expanded towards quadrant II and III may contribute to increase accuracy rate of tap touch interaction by allowing more room to touch considering the fact that they tend to hit towards those quadrants.

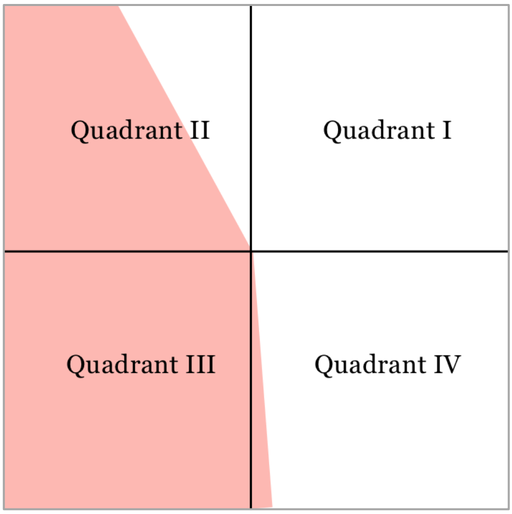

Figure 3-14 95% coverage area of angle for tap touch

3.4.3 Leveraging performance prediction models

Performance prediction models were established as in Table 3-4, Table 3-8, Table 3-12 and Table 3-16 for four performance measures. Most contributing variables were selected based on the percent amount of effect size of each variable. For task completion time, target size, age group, target X, and target Y along with square terms of target X and Y selected which yields adjusted the r-square value as 0.53. For distance to target, hand, target X and target Y were selected with adjusted r-square of 0.22. For angle to the X axis, age group, hand and target Y selected with adjusted r-square of 0.18. For speed accuracy ratio, target size, target X, target Y, age group and hand were selected with adjusted r-square of 0.26. It is interesting to note that only target Y was selected for angle prediction.

This result demonstrates that with the mixture of design-related variables and demographic variables, it is possible to predict each performance measures without conducting usability testing on design options. It will be an effective and efficient tool, especially when comparing multiple design options to predict which one will demonstrate better performance rather than used as evaluating absolute usability measures.

3.4.4 Recommended design strategies

Task completion time decreased as the target size grows, which means it feels easier to tap as target size becomes larger. In terms of user interface design within given space on display, the target size needs to be limited to some extent to capture all necessary touch interfaces in one screen state. Optimal target sizes will be proposed later section. It is also observed that there is a clear increasing tendency over age groups as it becomes older groups, task completion time increases. If we design a touch interface system targeting older age groups, it is suggested that use larger tap targets to allow them more generous task completion time thus easier to interact with. Since task completion time also decreased if it is closer to the center of the display, if there is a task requires faster completion time, we could consider placing critical touch elements of the task towards the center of the display.

3.4.5 Tap target size recommendation

Table 3-17 shows suggested target size based on accuracy measures we got from the experiment. While Park and Han (2010) suggested optimal touch target sizes to minimize error rates of given task, it is suggested that given touch result data and distance from the center of touch target in this study. From Figure 3-2, it is easily derived that how much of accuracy will be expected for different target sizes. Confidence level depicted in Figure 3-2 is for two tails, while we only need one tail so we could expect to achieve accuracy levels of 68 + 32/2 = 84% for 1 standard deviation, 95 + 5/2 = 97.5% for 2 standard deviation and 99.7 + 0.3/2 = 99.85% for 3 standard deviation.

Table 3-17 Suggested tap touch target sizes

Variables	Levels	Performance accuracy levels					
		1 SD 84%		2 SD 97.5%		3 SD 99.85%	
		pixel	**mm**	**pixel**	**mm**	**pixel**	**mm**
Hand	One	40.3	7.7	54.7	10.4	69.0	13.2
	Two	33.7	6.5	46.1	8.8	58.4	11.2
Age group	20s	39.0	7.5	53.1	10.1	67.2	12.8
	30s	36.8	7.0	50.2	9.6	63.7	12.2
	40s	35.4	6.8	48.1	9.2	60.7	11.6
	50s	36.9	7.1	50.4	9.6	63.9	12.2
	60s	36.0	6.9	48.8	9.3	61.7	11.8
Region	London	36.3	6.9	49.6	9.5	62.8	12.0
	Paris	37.3	7.1	50.9	9.7	64.5	12.3
	NY	37.3	7.1	51.0	9.7	64.6	12.3
	SF	38.2	7.3	52.0	9.9	65.8	12.6
Gender	Male	36.1	6.9	49.3	9.4	62.5	12.0
	Female	38.2	7.3	52.0	9.9	65.8	12.6
Target size (pixel)	36	36.8	7.0	50.3	9.6	63.7	12.2
	70	35.6	6.8	48.7	9.3	61.7	11.8
	106	38.6	7.4	52.5	10.0	66.4	12.7

Variables	Levels	Performance accuracy levels					
		1 SD 84%		2 SD 97.5%		3 SD 99.85%	
		pixel	**mm**	**pixel**	**mm**	**pixel**	**mm**
Target shapes	Circle	36.8	7.0	50.1	9.6	63.5	12.1
	Rectangle	37.8	7.2	51.5	9.8	65.3	12.5
Target X (pixel)	20	44.3	8.5	59.5	11.4	74.8	14.3
	60	40.6	7.8	54.9	10.5	69.2	13.2
	100	36.2	6.9	49.0	9.4	61.7	11.8
	140	34.5	6.6	47.2	9.0	59.9	11.5
	180	36.7	7.0	50.4	9.6	64.1	12.2
	220	31.5	6.0	42.9	8.2	54.4	10.4
Target Y (pixel)	20	43.7	8.4	59.1	11.3	74.5	14.2
	60	41.3	7.9	56.4	10.8	71.4	13.6
	100	37.5	7.2	50.9	9.7	64.3	12.3
	140	35.4	6.8	48.2	9.2	60.9	11.6
	180	35.1	6.7	47.7	9.1	60.2	11.5
	220	34.8	6.7	47.6	9.1	60.4	11.5
	260	37.4	7.2	51.2	9.8	65.01	12.4
	300	36.7	7.0	50.0	9.6	63.3	12.1
Average		**37.3**	**7.1**	**50.8**	**9.7**	**64.3**	**12.3**
Min		**31.5**	**6.0**	**43.0**	**8.2**	**54.5**	**10.4**
Max		**44.3**	**8.5**	**59.6**	**11.4**	**74.8**	**14.3**

From Table 3-17, we could come up with Table 3-18 to indicate the expected level of accuracy for each tap target sizes by interpolating the data points from Table 3-17. This is averaged results from all variables mixed together if it is needed to focus on any specific variable used in this study, it is easily derived from Table 3-17 as needed. This information will be useful to identify the expected performance level by knowing target sizes. Design decision could be made according to the priority or importance of touch element on a screen display based on the expected accuracy information. Table 3-18 shows expected accuracy level in percent for each target size. It is noted that if it goes above 12mm, we will get 100% accuracy, so it is not needed to design any touch element larger than 12mm.

Table 3-18 Expected accuracy levels per target sizes

Target sizes(mm)	Expected accuracy level(%)
6	82.5
7	85.6
8	88.6
9	91.6
10	94.7
11	97.7
12	100.0

Tapping angle shows that most subjects tap on quadrant III on the average. This may relate to the fact that we only investigated right-hand use in our analysis. If left-hand usage shows towards quadrant IV or I, we could induce that this tapping tendency is due to handedness. For right handed users, we could consider designing touch area a little bit skewed toward quadrant III not necessarily changing the physical design or size of the target in order to achieve more sensitive touch performance.

Figure 3-15 shows general speed accuracy tendency of tap touch experiment. Each dot indicates mean accuracy measure(X-axis) and mean speed measure(Y-axis) and the red line shows linear regression line of this plot. ($y=533.629-3.057x$) Though r square value is not high due to the large volume of data, it is shown that there is clear tendency of speed accuracy trade-off happening across all subjects participated.

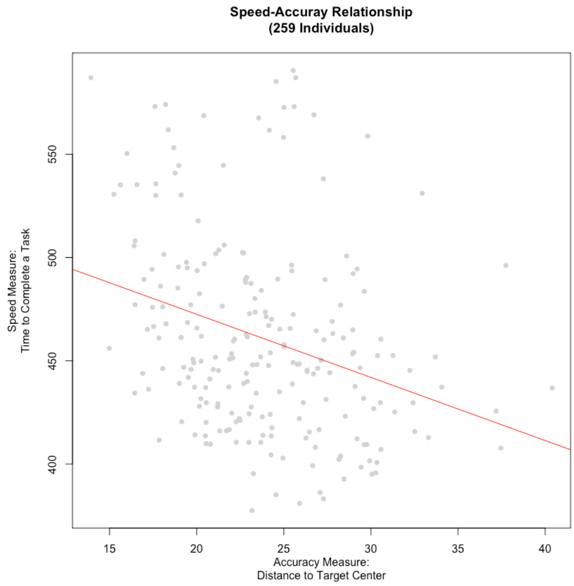

Figure 3-15 Speed accuracy tradeoff of tap touch

Chapter 4. Move touch experiment

4.1 Introduction

Move touch, by its definition, involves an object to move, the starting point and end point. One selects an object from starting point then moves it towards the end point while maintaining applied pressure on the object. This requires a certain level of force on the selected object from starting point to end point not to loose the object on the way. If one fails to apply required force along the line of movement, we consider that task as a failure and the object bounce back to its original position which is the starting point in most touch interface systems. This gesture is also widely used along with tap touch to support various user tasks as defined in Table 2-2 such as move an object from one position to another, bundle objects, or scrolling. One of the most popular examples of move touch is when you organize the application icons on iPhone in edit mode by pressing and holding any application icon(Figure 4-1).

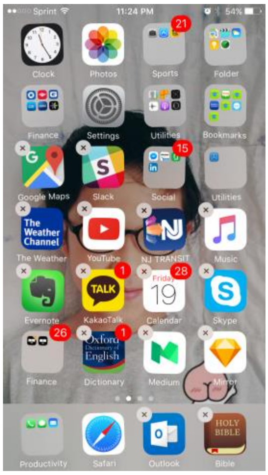

Figure 4-1 An example of move touch in iPhone's edit mode of applications

As it requires continuous force along the line of movement, we could expect that two hands setup will show better performance than one hand setup since two hands setup will be easier to maintain the force applied due to supporting hand. Unlike tap touch study, we will be able to leverage popular HCI theory, Fitts law for move touch experiment since it includes all elements of variables defined in Fitts law as in equation 2-1 which are movement distance, target size and movement time.

We will define four performance measures – velocity, accuracy and throughput then investigate them over a different set of variables. Although it is obvious to expect reduced throughput for one hand setup, it is meaningful to observe how speed-accuracy relationships change under different task conditions. Hypothetically, two hands setup will be more accurate as the index finger is thinner than the thumb (Siek, Rogers, & Connelly, 2005), while one hand setup can be faster because it requires less joint coordination (Tseng, Scholz, Schöner, & Hotchkiss, 2003). By investigating throughput and speed-accuracy relationships, we are expected to gain a global view of performance (Soukoreff & MacKenzie, 2004).

From the cognitive process perspective, move touch involves multiple levels of cognitive steps as following steps: 1) recognize the starting point, 2) recognize the end point, 3) plan movement, 4) move and touch the starting point, 5) move the object to the end point, 6) evaluate if the object is on the end point, 7) then release the object from finger.

Each of these steps will require mental processing thus more time to complete the task than just simple tap task. In this study, however, elapsed time from step 1 through 7 is captured all together, it would be difficult to investigate the effect of each step individually. Since it included all 7 cognitive steps, we will be able to evaluate the effect of overall impact on movement, not individual step. Looking into individual step level would be a good topic for a follow-up research question.

4.2 Methods

Move touch is the second most frequently used gesture for touch interface systems (Villamor, Willis & Wroblewski ,2010). Move touch typically used for moving an object on display from one place to another or in more generic form, for scrolling a list on a display which is both widely used touch gestures in a mobile context. Thus, a deeper understanding of this basic touch will benefit designers of touch interface systems to implement better and usable system. In order to achieve these goals, following tasks and experimental design were planned and executed with recruited subjects for this study.

4.2.1 Task design

The subjects were asked to conduct move tasks from the initial touch location to target touch locations, and system logged the initial touch points in x-y coordinates and additional in between trajectory points then final release point along with task completion time from initial touch to the final release of touch. This task is basically conform with original Fitts (1954) experimental setup with differences of using thumb and index finger as input methods, and movement directions are 2 dimensional whereas original Fitts' law covers only one-dimensional task with a stylus as an input device.

The input device had a 3.0-inch capacitive-type touch screen (Screen-to-Body Ratio: 51.7%, Resolution: 240×320 pixels), and its body size was 98mm×55mm×12.7mm with weight 100g. This is an identical device as in tap touch experiment.

The task interface was programmed on Microsoft Windows Mobile 6.1 platform. After a trial run, the log files were stored and retrieved in a text file format.

4.2.2 Experimental design

Figure 4-2 shows experimental setup for move touch tasks. There are two levels of target shapes(circle and rectangle) and three levels of target sizes(5mm, 10mm and 15mm). Initial touch targets were presented on four different locations NW(North West), NE(North East), SW(South West) and SE(South East). Once system presented one location from these four as a starting location, then subjects were asked to move that touch object to the other 3 locations respectively.

The total number of experiments for a subject was 144(=2x3x4x3x2) which is calculated by multiplying all possible levels of the experimental setup for touch targets(=2x3=6), the number of moves per position(=4x3=12) and the user postures(=2). The order of the task conditions was programmed to come out in random order and logged accordingly. To mitigate fatigue and uncontrolled variability, a subject visited two different days splitting the total number of repetition into the half. The subjects were given intermittent breaks in a span of an hour (Freivalds, 2009).

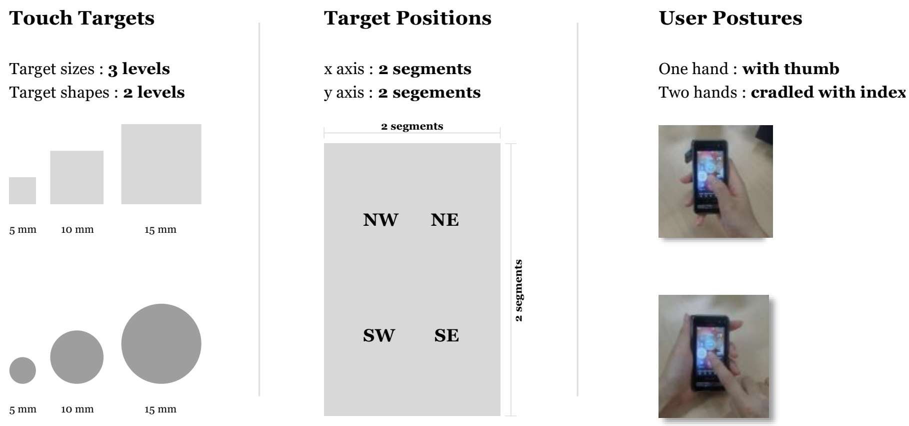

Figure 4-2 Experimental setups for move touch tasks

4.2.3 Subjects

Subject recruited for move touch study were the same group as tap touch experiment with the same setup of a lab environment. As in tap touch experiments, in order to mitigate the effect of fatigue, all test tasks were divided into two groups then conducted in two separate days of visit per subject. All other task conditions were identical as tap touch experiment.

4.3 Data analysis method

In order to answer established research questions for move touch experiment, we investigated the 4 performance measures defined in previous section – velocity(travel distance divided by elapsed time), accuracy of initial touch(distance from center of target to actual touch point on initial target), accuracy of final release(distance from center of final release point to actual release point), and performance throughput (Fitts,1954).

First, we have conducted Anderson-Darling normality check, Q-Q plot and histogram for all performance measures to confirm normality of the data set. Then contributing factors are identified via ANOVA analysis for all experimental variables associated, and TukeyHSD test was used to analyze the effect (Abdi & Williams, 2010). Partial eta squared was calculated to investigate the effect size of each variable to performance measures (Kirk, 1982; Tabachnick, Fidell, & Osterlind, 2001; Levine, 2002). It quantifies the effect size of a factor in a factorial experiment by a proportion of the total variability attributable to the factor (Nandy, 2012). We used boxplots to investigate overall tendency or visual patterns of each variable, along with actual data point tables with quantiles, mean and standard deviations to confirm actual amount of pattern if there is any. Finally, with all identified critical variables to performance measures, we will derive regression models to establish performance prediction models for each performance measure.

4.3.1 Data handling

A total of 27,648 data points were gathered for right handed experiments only. We assumed that any finding from right handed use could be flipped to left handed use. In order to handle outliers, we used interquartile range method (Faraway, 2002; Zhao, 2012). This was applied to velocity, the accuracy of initial touch and accuracy of the final release. This leaves us 26,761 data points about 3% reduction from initial data points.

Initial analysis indicated that individual variability needed to be addressed to increase the reliability of established model. In order to reduce inter-subject variability, we decided to aggregate data points as a single data point for each variable and level. This way, we reduced the number of data points down to 4,171 from initial 26,761.

4.3.2 Result

4.3.3 Normality check

As we did for tap touch experiment, we validated the normality of move touch data for each performance measures defined in the previous section – speed of task completion, the accuracy of initial touch, the accuracy of final release and throughput defined be Fitts law. Since we have a large volume of data for each measure, we cannot expect usual normality check like Anderson-Darling normality check or Q-Q plot(Figure 4-3) will conform normality of the data due to high variability caused by high volume of data. This doesn't mean we cannot assume the normality of our data, Figure 4-4 shows probability distribution plot on the histogram of aforementioned performance measures for move touch. According to the shapes of each density plot, we could assume the normality of our data set. Note these plots are aggregated from all levels of variables.

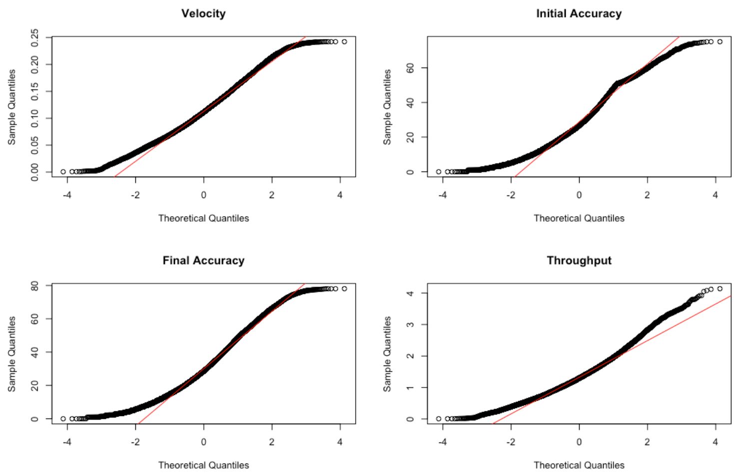

Figure 4-3 Anderson-Darling normality Q-Q plot for move touch

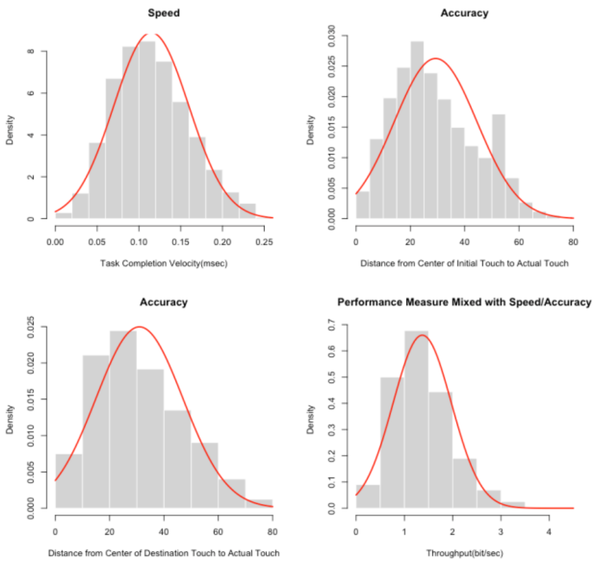

Figure 4-4 Probability distribution of speed(msec), the accuracy of initial touch(pixel), the accuracy of final release(pixel) and throughput from Fitts law(bit/sec)

4.3.4 Variables affecting task velocity on move touch

Table 4-1 contains ANOVA result as well as the effect size of each variable on task velocity of move touch. We verified any data trend observed visually from Figure 4-6, Figure 4-7 and Figure 4-8 and quantile, mean and standard deviation values are presented in Table 4-2 and Table 4-3 for all levels of independent variables. Hand posture(H), age group(A), region(R), initial Y(Y_i), final Y(Y_f), target size(S) and movement direction(D) have statistically significant effect on task velocity for move touch. Gender(G), initial X(X_i), final X(X_f) and target shape don't have an influence on task velocity. For variables statistically significant on task velocity, TukeyHSD test was conducted to investigate detail influences for each level of the variable.

For hand posture, two hands(0.123 pixels/msec) had a larger value than one hand(0.106 pixels/msec). We defined task velocity as the distance between the initial touch point and final release point divided by total elapsed time and chose as one of performance measure of move touch. For velocity itself, it tells us how fast subjects can complete a given move task. As we verified from ANOVA, one hand(0.106pixcel/msec) and two hands(0.123 pixels/msec) experimental setup showed a significantly different result in task velocity, two hands being around 14% faster than one hand on the average. This may be due to the inherent task characteristics itself, subjects need to maintain a certain level of force applied on the display surface until they complete the task. In this condition, two hands setup may give them more supporting than one hand setup making them easier to move thus resulting in faster movement. This is counter intuitive what we have learned from tap touch experiment regarding handedness mostly due to the inherent difference in task characteristics.

In terms of age group, it is observed that there is decreasing tendency as it becomes older groups(slight negative slope of -6.310e-04 with $p<0.001$ confidence level from linear modeling) This also confirms our common sense that younger people will make faster movement under the same task condition.

As to regional factors, it is interesting to note that London(0.119 pixels/sec) and San Francisco(0.119 pixels/sec) showed the highest value while Paris(0.113 pixels/msec) and New York(0.108 pixels/msec) behind. In general, it seems Europeans controls touch movement faster than those who reside in the US by around 2% on the average. Even though it is identified that regional factor proven to be statistically significantly affecting task velocity, considering the absolute amount of difference (2% on the average) may make this not considerable factor for task velocity.

It is interesting to note that only Y coordinates(both initial and final) have a significant effect on task velocity. This means task velocity varies across Y axis not affect by X axis.

Target size shows a increasing tendency of velocity as target size grows(3% increase grow from smallest to medium, 5% increase from medium to large on the average).

In theory, there would be no clear dependency of moving speed over object shapes because once the grip on the object established firmly, object size may not be critical to complete the moving task. There might be two factors associated with this – psychological or physical factor. Psychologically, we could explain this phenomenon that larger targets would give the subject more comfortable feeling in grabbing the target thus resulting in faster movement. From physical constraint perspective, there might be slight slippery happening while the subject is moving the object, requiring them to maintain applied force on the object not to loose contact with the object. In this case, if the target is larger, it would be less error-prone since it covers more area thus even the subject slips a little bit, larger contact area helps to recover the micro slippery from completely failing the task thus resulting in faster movement.

For moving directions, we can observe a pattern that diagonal directions(NE,NW,SE,SW) are showing faster velocity over vertical or horizontal directions(N,E,S,W). In order to verify that this is not due to biomechanical constraints for one hand setup since the data is aggregated, we plotted the following boxplot to compare between one hand and two hands setup separately.

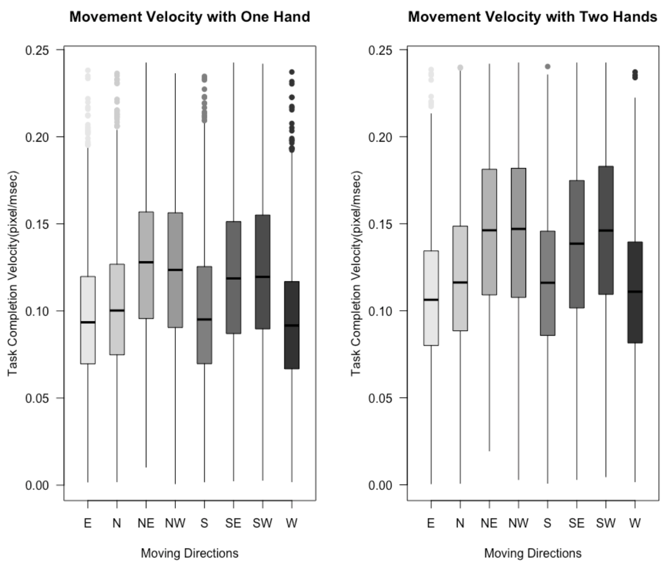

Figure 4-5 Boxplot comparison for task velocity about moving directions between one hand and two hands setup

Figure 4-5 still shows the same pattern as we observed from aggregated boxplot. This means this pattern is not due to hand postures rather it is pattern occurred from moving direction itself. It is interesting to note that two hands setup shows faster speed for all moving directions over one hand setup. From this, we could infer that diagonal moving task is easier to conduct compared to recti-directions.

Table 4-1 ANOVA and effect size(partial eta squared) of task completion velocity for move touch

	η_p^2	Sum Sq	Df	F value	Pr(>F)
Hand(H)	0.143	0.27397	1	692.6763	< 2e-16***
Age group(A)	0.190	0.38585	4	243.8897	< 2e-16***
Region(R)	0.065	0.11463	3	96.6037	< 2e-16***
Gender(G)	0.000	0.00130	1	3.2932	0.06964
Initial X(X_i)	0.000	0.00026	1	0.6655	0.41468
Initial Y(Y_i)	0.110	0.20369	1	514.9955	< 2e-16***
Final X(X_f)	0.000	0.00119	1	3.0188	0.08238
Final Y(Y_f)	0.102	0.18600	1	470.2669	< 2e-16***
Object Size(S)	0.044	0.07485	2	94.6229	< 2e-16***
Object Shape(P)	0.000	0.00057	1	1.4442	0.22953
Move Direction(D)	0.325	0.78934	7	399.1426	< 2e-16***
Residuals		1.64100	4149		

*** P-value < 0.001, ** P-value < 0.01, * P-value < 0.05

Table 4-2 Quantile, mean and standard deviation of task completion velocity of demography and interaction related variables for move touch

Variables	Levels	Quantile					Mean(SD)
		0%	**25%**	**50%**	**75%**	**100%**	
Hand	One	0	0.07	0.10	0.13	0.24	0.10(0.04)
	Two	0	0.08	0.12	0.15	0.24	0.12(0.04)
Age group	20s	0	0.09	0.12	0.16	0.24	0.13(0.04)
	30s	0	0.08	0.10	0.14	0.24	0.11(0.04)
	40s	0	0.09	0.11	0.14	0.23	0.12(0.03)
	50s	0	0.07	0.10	0.13	0.24	0.10(0.04)
	60s	0	0.10	0.11	0.13	0.18	0.11(0.02)
Region	London	0	0.08	0.11	0.14	0.24	0.11(0.04)
	Paris	0	0.08	0.10	0.14	0.24	0.11(0.04)
	NY	0	0.07	0.10	0.13	0.24	0.10(0.04)
	SF	0	0.08	0.11	0.14	0.24	0.11(0.04)
Gender	Male	0	0.08	0.11	0.14	0.24	0.11(0.04)
	Female	0	0.08	0.10	0.14	0.24	0.11(0.04)

Table 4-3 Quantile, mean and standard deviation of task completion velocity of design-related variables for move touch

Variables	Levels	Quantile					Mean(SD)
		0%	**25%**	**50%**	**75%**	**100%**	
Target size (pixel)	36	0	0.07	0.10	0.13	0.24	0.10(0.04)
	70	0	0.08	0.11	0.14	0.24	0.11(0.04)
	106	0	0.08	0.11	0.15	0.24	0.11(0.04)
Target shapes	Circle	0	0.08	0.11	0.14	0.24	0.11(0.04)
	Rectangle	0	0.08	0.11	0.14	0.24	0.11(0.04)
Initial X (pixel)	60	0	0.08	0.11	0.14	0.24	0.11(0.04)
	180	0	0.08	0.11	0.14	0.24	0.11(0.04)
Initial Y (pixel)	80	0	0.08	0.11	0.14	0.24	0.11(0.04)
	210	0	0.08	0.11	0.14	0.24	0.11(0.04)
Final X (pixel)	60	0	0.08	0.11	0.14	0.24	0.11(0.04)
	180	0	0.08	0.11	0.14	0.24	0.11(0.04)
Final Y (pixel)	80	0	0.08	0.11	0.14	0.24	0.11(0.04)
	210	0	0.08	0.11	0.14	0.24	0.11(0.04)
Moving Direction	E	0	0.07	0.10	0.12	0.23	0.10(0.03)
	W	0	0.07	0.10	0.12	0.23	0.10(0.03)
	S	0	0.07	0.10	0.13	0.24	0.10(0.04)
	N	0	0.08	0.10	0.13	0.23	0.11(0.04)
	NE	0	0.10	0.13	0.16	0.24	0.13(0.04)
	NW	0	0.09	0.13	0.17	0.24	0.13(0.04)
	SE	0	0.09	0.12	0.16	0.24	0.13(0.04)
	SW	0	0.09	0.13	0.17	0.24	0.13(0.04)

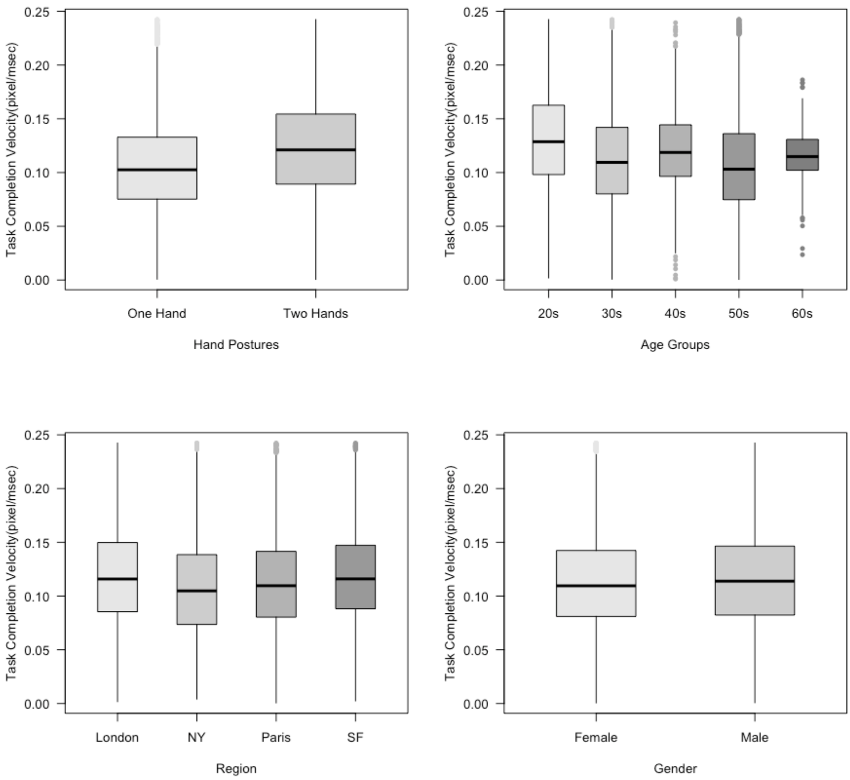

Figure 4-6 Boxplots of demography and interaction related variables regarding task completion velocity for move touch

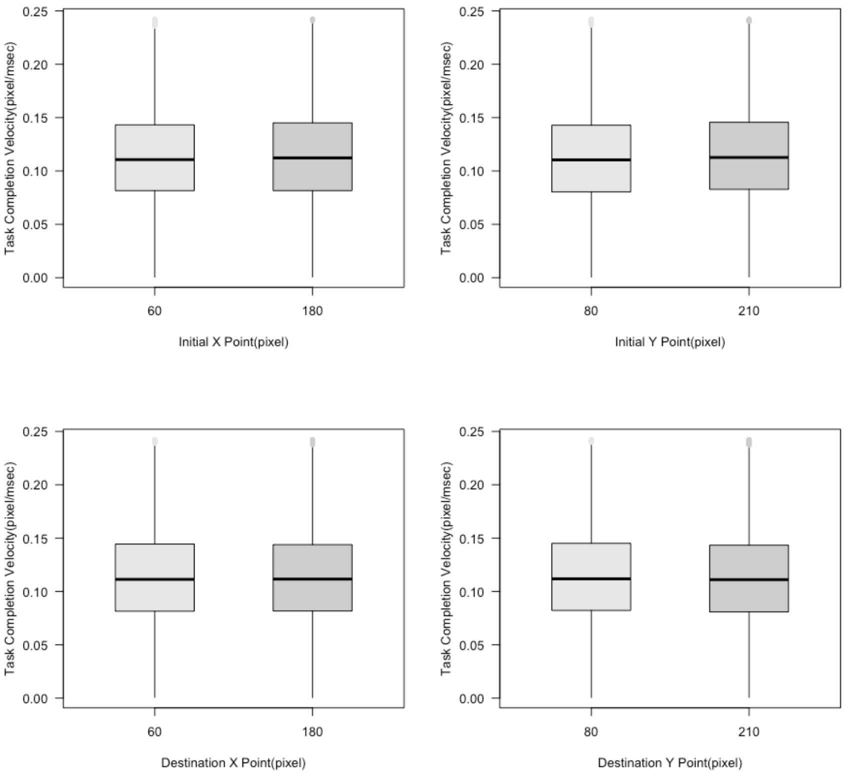

Figure 4-7 Boxplots of design-related variables regarding task completion velocity for move touch. (at initial and destination points)

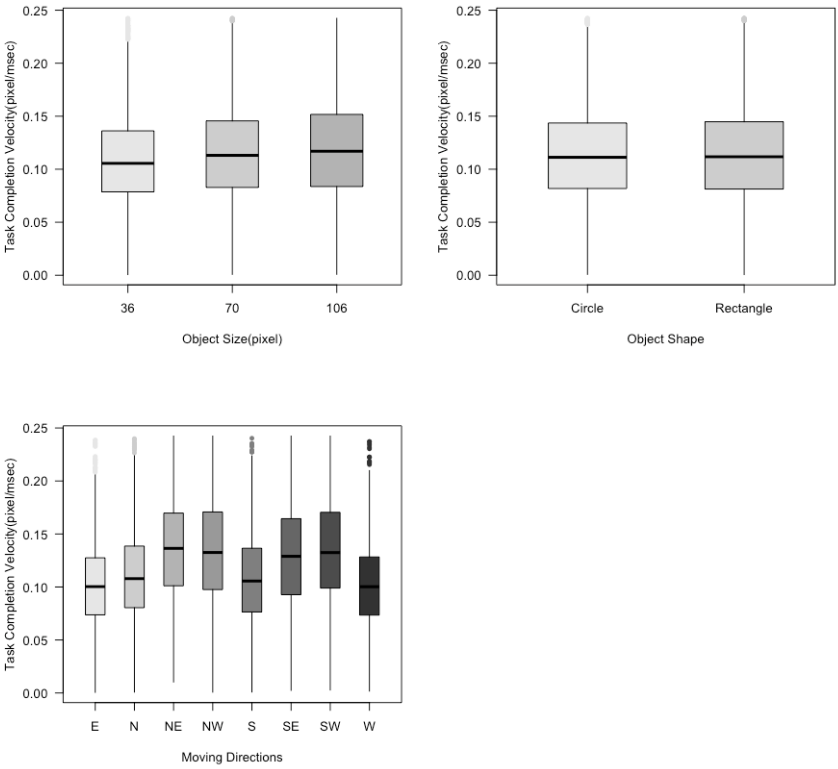

Figure 4-8 Boxplots of design-related variables regarding task completion velocity for move touch. (object size, shape and moving directions)

Investigating effect size of each variable for task velocity will allow us to identify how much of contribution of each variable affecting the performance. We can also investigate relative contribution amount by calculating the ratio of effect size. By order of percent contribution, movement direction(33.2%) showed the most value followed by age group(19.4%), hand posture(14.6%), initial Y(11.2%), final Y(10.4%), region(6.5%) and target size(4.5%).

Target shape, gender, initial X and final X showed 0% effect on task velocity. This matches with the ANOVA and TukeyHSD result in that contributing factors are identified as statistically significant. Region and target size didn't make it in to performance prediction model as in Table 4-4 since they have relatively less impact compared to other variables(less than 10% effect) and identified yielding less significant regression model.

Table 4-4 Prediction model of velocity for move touch

	Estimated	Std Error	t-value	Pr(>|t|)
(Intercept)	1.142e-01	2.014e-03	55.184	< 2e-16***
Y_i	-2.406e-04	1.127e-05	-21.339	< 2e-16***
Y_f	2.517e-04	1.127e-05	22.322	< 2e-16***
A	-5.893e-04	2.590e-05	-24.462	< 2e-16***
H: Two hands	1.620e-02	6.400e-04	25.318	< 2e-16***
D: N	4.083e-02	2.073e-03	19.696	< 2e-16***
D: NE	6.768e-02	2.216e-03	30.545	< 2e-16***
D: NW	6.497e-02	2.217e-03	29.298	< 2e-16***
D: S	-2.619e-02	1.357e-03	-19.298	< 2e-16***
D: SE	-3.399e-03	1.568e-03	-2.168	0.0302*
D: W	6.888e-04	1.108e-03	0.621	0.5343
Residual standard error: 0.02189 on 4160 degrees of freedom				
Multiple R-squared: 0.394, Adjusted R-squared: **0.3926**				
F-statistic: 270.5 on 10 and 4160 DF, p-value: < 2.2e-16				

*** P-value < 0.001, ** P-value < 0.01, * P-value < 0.05

4.3.5 Variables affecting accuracy of initial touch on move touch

Table 4-5 contains ANOVA result as well as the effect size of each variable accuracy of initial touch. We verified any data trend observed visually from Figure 4-9, Figure 4-10 and Figure 4-11 and quantile, mean and standard deviation values are presented in Table 4-6 and Table 4-7 for all levels of independent variables. It is observed that all the variables associated with the performance measure proved to be statistically significant.

Table 4-5 ANOVA and effect size(partial eta squared) of the accuracy of initial touch for move touch

	η_p^2	Sum Sq	Df	F value	Pr(>F)
Hand(H)	0.129	32844	1	618.5647	< 2e-16***
Age group(A)	0.057	13428	4	63.2245	< 2e-16***
Region(R)	0.017	3917	3	24.5936	< 2e-16***
Gender(G)	0.042	9790	1	184.3890	< 2e-16***
Initial X(X_i)	0.196	53934	1	1015.7805	< 2e-16***
Initial Y(Y_i)	0.021	4776	1	89.9513	< 2e-16***
Final X(X_f)	0.005	1230	1	23.1628	< 2e-16***
Final Y(Y_f)	0.001	365	1	6.8805	< 2e-16***
Object Size(S)	0.018	4050	2	38.1347	< 2e-16***
Object Shape(P)	0.002	634	1	11.9341	< 2e-16***
Move Direction(D)	0.041	9424	7	35.4968	< 2e-16***
Residuals		220297	4149		

*** P-value < 0.001, ** P-value < 0.01, * P-value < 0.0

For hand posture, two hands(26.52 pixel) showed around 20% more accurate result than one hand(32.06 pixels) which conforms past research around handedness. Since two handed posture provides more firm support to complete a move task, it generally allows users to get more accurate touch result compared to one hand posture.

For age group and region, no specific pattern or tendency was observed. For gender, the male group showed around 11% more accurate result than the female group which can be explained from previous findings that female group tends to focus on speed than accuracy.

For initial and final coordinates, both shows significance over initial touch, but it is more reasonable to consider only initial touch points. The accuracy of initial touch points regarding initial touch points shows that lower left corner initial points produced a more accurate result than upper right corner points. For one hand setup, this could mean that extension of thumb would be easier to control the initial tap target than flexing the thumb. For two hands setup, assuming index finger residing on the center of the screen where subjects could minimize travel distance for all directions, the lower left corner will give them more visibility than other points since we evaluated only right-handed data points. For all another point, right hand may block the position thus making it harder to locate thus resulting in less accuracy. Since initial touch point decides the final release points, it is reasonable to observe opposite result on final release points which shows the best accuracy on top right corner of the screen which would be destination points from bottom left corner points. There might be some cognitive effect on performance due to the planning of movement towards target point, it may be safe to assume that it is negligible. Effect size data also supports this since final points' effect sizes are far less than initial points.

Table 4-6 Quantile, mean and standard deviation of the accuracy of initial touch of demography and interaction related variables for move touch

Variables	Levels	Quantile					Mean(SD)
		0%	**25%**	**50%**	**75%**	**100%**	
Hand	One	0	19.7	30.0	45.0	75.0	32.0(15.6)
	Two	0	16.0	24.1	35.0	74.6	26.5(14.1)
Age group	20s	0	16.7	24.8	36.0	73.5	27.3(14.2)
	30s	0	17.2	26.2	39.2	74.5	28.8(15.0)
	40s	1	15.2	22.8	34.3	72.0	26.0(14.5)
	50s	0	18.6	28.4	43.1	75.0	30.7(15.6)
	60s	2	16.0	23.9	34.3	60.2	25.0(12.7)
Region	London	0	17.2	26.1	39.2	74.7	28.8(15.1)
	Paris	0	17.4	26.4	39.6	75.0	29.0(15.1)
	NY	0	17.0	26.2	40.2	75.0	29.0(15.4)
	SF	0	19.1	28.3	41.4	75.0	30.4(14.9)
Gender	Male	0	16.5	24.8	36.6	74.7	27.4 (14.5)
	Female	0	18.7	28.4	43.0	75.0	30.8(15.5)

For target size, it becomes more accurate as target size becomes smaller which aligns with previous findings and research. The effect size of target shape is also small enough to ignore. Even though there is no clear tendency observed for movement direction on initial accuracy, it is interesting to note that movement direction has some impact on initial touch accuracy which may be related to aforementioned cognitive task planning.

Table 4-7 Quantile, mean and standard deviation of the accuracy of initial touch of design-related variables for move touch

Variables	Levels	Quantile					Mean(SD)
		0%	**25%**	**50%**	**75%**	**100%**	
Target size (pixel)	36	0	16.9	25.5	38.2	75.0	28.1(14.8)
	70	0	17.2	26.1	39.6	74.7	29.0(15.2)
	106	0	19.0	28.4	42.1	74.6	30.6(15.4)
Target shapes	Circle	0	17.2	26.1	39.4	75.0	28.8(15.0)
	Rectangle	0	17.8	27.2	41.0	75.0	29.7(15.3)
Initial X (pixel)	60	0	16.5	25.1	36.3	75.0	27.4(14.4)
	180	0	18.8	28.6	44.8	75.0	31.1(15.6)
Initial Y (pixel)	80	0	17.0	27.8	42.4	75.0	30.0(15.8)
	210	0	18.0	25.6	37.6	75.0	28.5(14.4)
Final X (pixel)	60	0	21.1	32.0	47.1	75.0	33.4(15.3)
	180	0	15.0	22.8	32.7	75.0	25.1(13.7)
Final Y (pixel)	80	0	19.6	28.2	41.2	75.0	30.5(14.7)
	210	0	15.8	25.0	38.9	75.0	28.0(15.4)
Moving Direction	E	0	13.6	21.4	33.1	74.2	24.5(14.3)
	W	0	21.9	35.4	51.1	74.2	35.4(15.9)
	S	1	17.2	26.9	38.4	74.7	28.7(14.9)
	N	0	20.6	28.2	38.2	75.0	30.2(13.7)
	NE	0	18.2	24.5	33.3	75.0	26.8(12.8)
	NW	1.41	18.6	27.5	40.9	74.2	29.9(14.7)
	SE	0	13.0	20.6	30.4	74.2	22.8(13.2)
	SW	0	19.8	33.5	51.0	75.0	33.8(16.5)

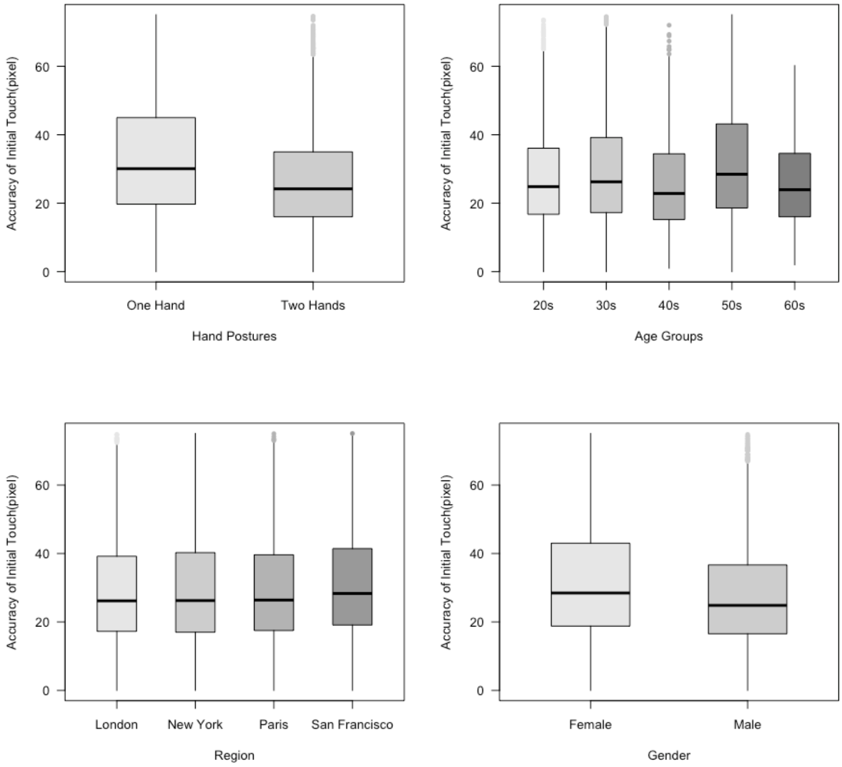

Figure 4-9 Boxplots of demography and interaction related variables regarding the accuracy of initial touch for move touch

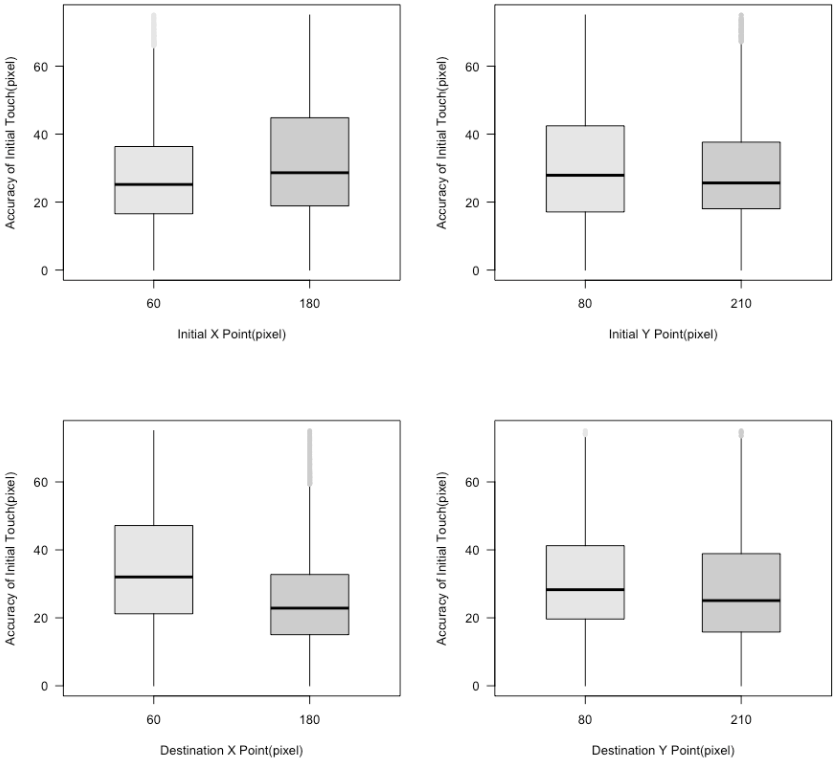

Figure 4-10 Boxplots of design-related variables regarding the accuracy of initial touch for move touch.(regarding initial and destination points)

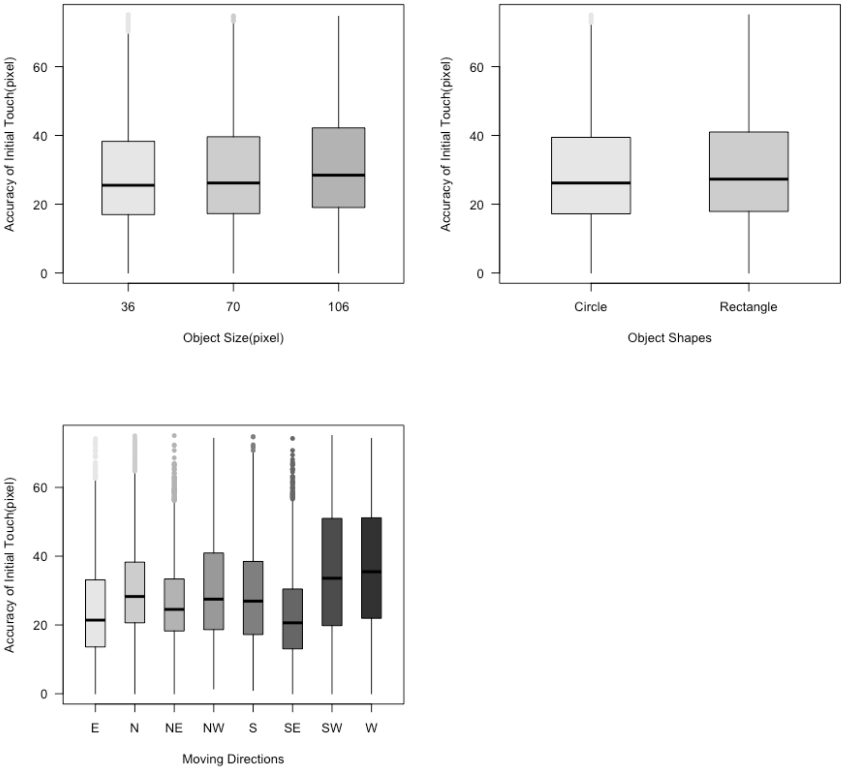

Figure 4-11 Boxplots of design-related variables regarding the accuracy of initial touch for move touch. (object size, shape and moving directions)

Investigating effect size of each variable for the accuracy of initial touch will allow us to identify how much of contribution of each variable affecting the performance. We can also investigate relative contribution amount by calculating the ratio of effect size. By order of percent contribution, initial X(37.1%) showed the most value followed by hand(24.4%), age group(10.8%), gender(7.9%), movement direction(7.8%), initial Y(4.0%), target size(3.4%), region(3.2%), final X(0.9%), target shape(0.4%) and final Y(0.2%). Among these variables, we have selected top 4 variables in terms of relative effect size – initial X, age group, hand, and gender as in Table 4-8.

Table 4-8 Prediction model of accuracy of initial touch for move touch

	Estimated	Std Error	t-value	Pr(>|t|)
(Intercept)	37.643	0.468	80.40	< 2e-16***
X_i	-0.067	0.002	-33.20	< 2e-16***
A	0.100	0.009	10.21	< 2e-16***
H: Two hands	-5.605	0.244	-22.90	< 2e-16***
G: Male	-3.418	0.245	-13.92	< 2e-16***
Residual standard error: 7.905 on 4166 degrees of freedom				
Multiple R-squared: 0.3139, Adjusted R-squared: **0.3132**				
F-statistic: 476.5 on 4 and 4166 DF, p-value: < 2.2e-16				

*** P-value < 0.001, ** P-value < 0.01, * P-value < 0.05

4.3.6 Variables affecting accuracy of final release on move touch

Table 4-9 contains ANOVA result as well as the effect size of each variable on the accuracy of the final release. We verified any data trend observed visually from Figure 4-12, Figure 4-13 and Figure 4-14 and quantile, mean and standard deviation values are presented in Table 4-10 and Table 4-11 for all levels of independent variables. Only initial X and target shape are not significant factors contributing accuracy of the final release. TukeyHSD test was conducted to investigate detail influences for each level of the variable. For hand posture, two hands(27.20 pixels) showed more accurate result than one hand(34.76 pixels) which is the similar result as initial touch.

Two hands posture shows more accurate result than one hand setup due to biomechanical or physical constraints posed by one hand setup while two hands setup doesn't have it since it has supporting hand to grip the device. However, the amount of difference between the two setups are larger than initial touch(one hand setup being 34.76 pixels and two hands setup being 27.20 pixels on their average thus 22% difference. This is 5% more than the difference on initial touch). This can be explained as fatigue factor while traveling from initial touch to final release on top of biomechanical or physical constraints mentioned before, since two hands setup has more support on grip with left hand, even when it reaches to final release point, subject could control better than the one hand setup since workloads are distributed across two hands thus give more control on index finger gesture.

Age groups, regions and gender show almost identical pattern as the accuracy of initial touch. A slight increasing tendency on age groups was observed as they get older groups while no clear pattern or differences observed on regions and gender in terms of the amount of measure.

For accuracy around initial touch points, there is no clear pattern observed for the accuracy of final release which is expected. For final release points, bottom right corner shows the most accurate result while top left corner shows the least accurate result.

For target size, it is barely observed increasing tendency while target size grows. We could conclude that the amount of effect of target size on final release accuracy is negligible as well as target shapes. There is no clear pattern observed for moving directions, since the accuracy of final release may not be impacted by the trajectory before it is released.

Table 4-9 ANOVA and effect size(partial eta squared) of the accuracy of final release for move touch

	η_p^2	Sum Sq	Df	F value	Pr(>F)
Hand(H)	0.202	57928	1	1048.2546	< 2e-16***
Age group(A)	0.096	24234	4	109.6340	< 2e-16***
Region(R)	0.018	4206	3	25.3689	< 2e-16***
Gender(G)	0.018	4297	1	77.7652	< 2e-16***
Initial X(X_i)	0.000	1	1	0.0188	0.8909
Initial Y(Y_i)	0.000	1741	1	31.5034	< 2e-16***
Final X(X_f)	0.089	22573	1	408.4879	< 2e-16***
Final Y(Y_f)	0.006	1474	1	26.6773	< 2e-16***
Object Size(S)	0.007	1787	2	16.1724	< 2e-16***
Object Shape(P)	0.000	208	1	3.7556	0.0527
Direction(D)	0.009	2090	7	7.5651	< 2e-16***
Residuals		220297	4149		

*** P-value < 0.001, ** P-value < 0.01, * P-value < 0.05

Table 4-10 Quantile, mean and standard deviation of accuracy of final release of demography and interaction related variables for move touch

Variables	Levels	Quantile					Mean(SD)
		0%	**25%**	**50%**	**75%**	**100%**	
Hand	One	0	21.9	33.3	46.8	78.0	34.7(16.4)
	Two	0	16.1	25.0	36.0	78.0	27.2(14.5)
Age group	20s	0	18.0	27.1	38.1	78.0	29.1(14.7)
	30s	0	17.2	26.9	39.6	77.7	29.2(15.4)
	40s	1	16.1	24.0	35.0	76.4	27.0(15.0)
	50s	0	20.0	31.2	45.1	78.0	33.1(16.6)
	60s	7.0	21.8	31.0	38.7	58.1	31.0(11.9)
Region	London	0	18.9	29.0	42.0	78.0	31.3(16.0)
	Paris	0	18.0	28.0	41.3	78.0	30.5(16.1)
	NY	0	17.4	27.5	40.1	77.4	29.7(15.6)
	SF	0	20.1	30.5	43.2	78.0	32.5(15.9)
Gender	Male	0	17.9	27.4	39.8	77.7	29.7(15.4)
	Female	0	19.2	29.8	43.2	78.0	31.9(16.3)

Table 4-11 Quantile, mean and standard deviation of the accuracy of the final release of design-related variables for move touch

Variables	Levels	Quantile					Mean(SD)
		0%	**25%**	**50%**	**75%**	**100%**	
Target size (pixel)	36	0	18.3	27.8	40.3	78.0	30.1(15.3)
	70	0	18.3	28.2	41.3	78.0	30.7(15.9)
	106	0	19.0	30.0	43.5	78.0	32.0(16.5)
Target shapes	Circle	0	18.6	28.4	41.2	78.0	30.7(15.7)
	Rectangle	0	18.3	28.7	42.0	78.0	31.1(16.2)
Initial X (pixel)	60	0	18.0	27.7	39.8	78.0	29.7(15.2)
	180	0	19.2	29.7	44.0	78.0	32.2(16.5)
Initial Y (pixel)	80	0	18.3	28.3	41.3	78.0	30.7(15.8)
	210	0	18.7	28.8	41.8	78.0	31.2(16.1)
Final X (pixel)	60	0	21.9	32.0	45.4	78.0	34.0(16.2)
	180	0	16.2	25.1	37.6	78.0	27.8(15.0)
Final Y (pixel)	80	0	20.6	31.4	44.2	78.0	33.1(16.1)
	210	0	17.0	26.2	38.6	78.0	28.8(15.4)
Moving Direction	E	0	15.6	24.4	36.4	77.0	26.9(14.7)
	W	0	20.6	31.6	46.5	78.0	33.9(16.9)
	S	0	17.8	26.6	38.0	78.0	29.0(14.8)
	N	1	20.4	30.8	43.1	78.0	32.6(16.0)
	NE	1	19.5	29.4	41.3	77.4	31.0(14.9)
	NW	1	23.3	34.2	48.4	77.6	36.1(16.9)
	SE	0	15.2	23.5	35.6	76.4	26.3(14.7)
	SW	0	20.5	31.6	45.8	77.4	33.3(16.1)

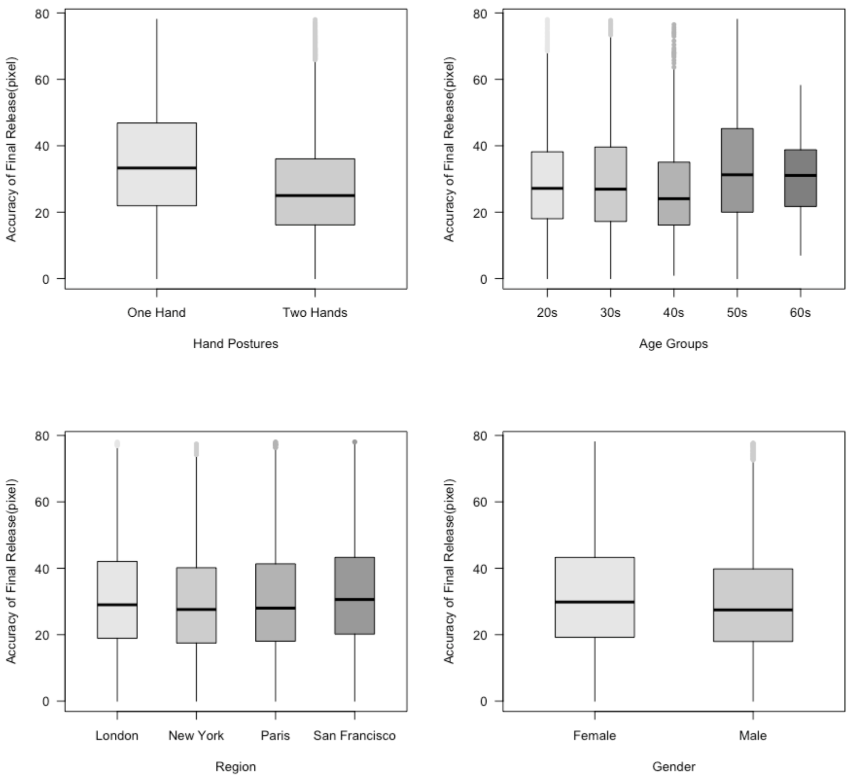

Figure 4-12 Boxplots of demography and interaction related variables regarding accuracy of final release for move touch

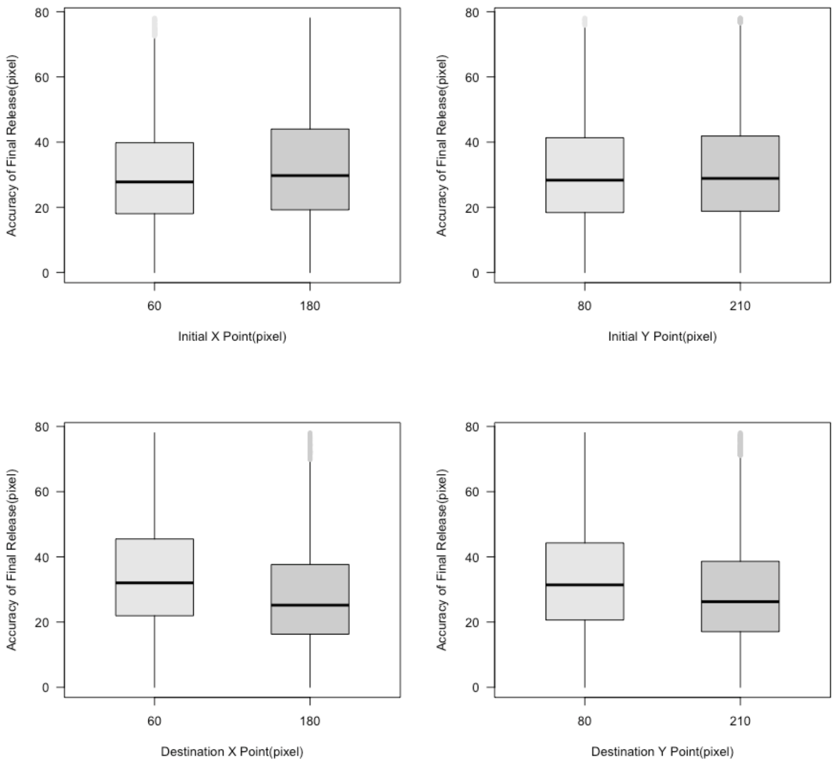

Figure 4-13 Boxplots of design-related variables regarding the accuracy of final release for move touch. (regarding initial and destination points)

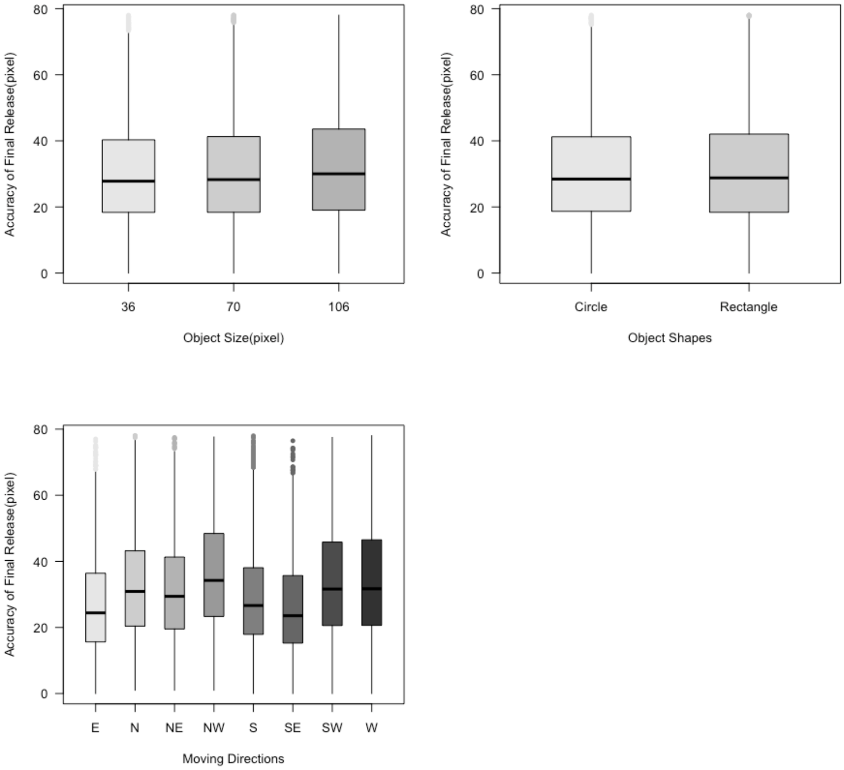

Figure 4-14 Boxplots of design-related variables regarding the accuracy of final release for move touch. (object size, shape and moving directions)

Investigating effect size of each variable for the accuracy of final release will allow us to identify how much of contribution of each variable affecting the performance. We can also investigate relative contribution amount by calculating the ratio of effect size. By order of percent contribution, hand(45.4%) showed the most value followed by age group(21.6%), final X(20.0%), region(4.0%), gender(4.0%), movement direction(2.0%), target size(1.6%) and final Y(1.3%). Target shape and initial X and Y showed 0% contribution. Among these variables, we selected top 3 variables – hand(H), age group(A), and final X(X_f) to be included in the final performance prediction model as depicted in Table 4-12.

Table 4-12 Prediction model of accuracy of final release for move touch

	Estimated	Std Error	t-value	Pr(>|t|)
(Intercept)	25.664	0.594	43.203	< 2e-16***
X_f	0.016	0.002	7.261	4.56e-13***
A	0.134	0.010	12.623	< 2e-16***
H: Two hands	-7.448	0.265	-28.060	< 2e-16***
Residual standard error: 8.572 on 4166 degrees of freedom				
Multiple R-squared: 0.1968, Adjusted R-squared: **0.196**				
F-statistic: 255.1 on 3 and 4166 DF, p-value: < 2.2e-16				

*** P-value < 0.001, ** P-value < 0.01, * P-value < 0.05

4.3.7 Variables affecting throughput on move touch

Throughput(bit/sec) as defined by Fitts law (Fitts, 1954) is used to determine the overall human performance of reciprocal movement. By its definition, it includes the variables of the velocity of moving between the two points as well as the distance. It is interesting to note that the ANOVA results of velocity and throughput show a similar pattern with slight different confidence levels.

Gender, initial X, final X, final Y and object shapes are all identified as non-affecting variables for velocity while only initial X showed significance on throughput. However, since initial X on throughput is significant, distance factor may have a small impact on throughput in general. By its definition, throughput includes all factors of velocity, only distance taken as logarithmic value over movement time, it is expected that there is a certain level of correlation between velocity and throughput. In fact, the correlation coefficient between the two values is 0.77 which indicates a strong positive relationship.

Table 4-13 contains ANOVA result as well as the effect size of each variable on throughput. We verified any data trend observed visually from Figure 4-15, Figure 4-16 and Figure 4-17 and quantile, mean and standard deviation values are presented in Table 4-14 and Table 4-15 for all levels of independent variables. Hand posture(H), age group(A), region(R), initial Y(Yi), final Y(Yf), target size(S) and movement direction(D) statistically significant effect on throughput for move touch. Gender, initial X, final X and target shape don't have an influence on throughput. For variables statistically significant on throughput, TukeyHSD test was conducted to investigate detail influences for each level of the variable.

Two hands setup(1.47 bit/sec) shows better performance over one hand setup(1.26 bit/sec) by 14%. This conforms with aforementioned performance results. For age groups, it is difficult to conclude that there is a clear decreasing tendency as age group becomes older. Same could be applied to regions and gender variables as well. We could assume that one hand and two hands setup is the most contributing factor among interaction and demography related variables. The result for initial touch and final release shows almost flat which is expected since, by definition of throughput, there is no contributing factor from these touch or release points to throughput measure.

Table 4-13 ANOVA and effect size(partial eta squared) of throughput for move touch

	η_p^2	Sum Sq	Df	F value	Pr(>F)
Hand(H)	0.145	40.92	1	701.4686	< 2e-16***
Age group(A)	0.182	53.78	4	230.4704	< 2e-16***
Region(R)	0.062	16.17	3	92.3870	< 2e-16***
Gender(G)	0.000	0.06	1	1.0636	0.30246
Initial X(X_i)	0.000	0.19	1	3.2555	0.07126
Initial Y(Y_i)	0.014	3.42	1	58.6919	< 2e-16***
Final X(X_f)	0.000	0.02	1	0.2757	0.59955
Final Y(Y_f)	0.018	4.49	1	76.8998	< 2e-16***
Object Size(S)	0.625	404.23	2	3464.4414	< 2e-16***
Object Shape(P)	0.000	0.08	1	1.3127	0.25197
Direction(D)	0.064	16.70	7	57.2522	< 2e-16***
Residuals		242.05	4149		

*** P-value < 0.001, ** P-value < 0.01, * P-value < 0.05

There is a clear decreasing tendency over target size up to 42% on the average from smallest(1.02 bit/sec) to largest(1.77 bit/sec). This is complete opposite result from velocity over the same variable. This could be explained by the third factor which is target size. As target size grows, index of difficulty(ID) becomes smaller by its definition, thus resulting in poor performance. The target shapes are not contributing factor as we noticed from other performance measures. For moving directions, we could observe the same pattern as in velocity, diagonal directions show higher performance than horizontal or vertical movement directions.

Table 4-14 Quantile, mean and standard deviation of throughput of demography and interaction related variables for move touch

Variables	Levels	Quantile					Mean(SD)
		0%	**25%**	**50%**	**75%**	**100%**	
Hand	One	0	0.86	0.10	1.59	4.14	1.26(0.55)
	Two	0	1.02	1.41	1.84	4.08	1.47(0.62)
Age group	20s	0.02	1.13	1.49	1.91	4.14	1.57(0.62)
	30s	0	0.91	1.27	1.69	3.80	1.34(0.59)
	40s	0	1.07	1.37	1.81	3.55	1.44(0.55)
	50s	0	0.85	1.21	1.63	4.12	1.28(0.57)
	60s	0.23	1.07	1.34	1.69	2.17	1.37(0.39)
Region	London	0.01	0.98	1.36	1.77	4.08	1.41(0.60)
	Paris	0	0.92	1.26	1.71	4.14	1.35(0.60)
	NY	0.03	0.85	1.22	1.65	4.12	1.29(0.59)
	SF	0.02	1.01	1.35	1.76	4.05	1.43(0.60)
Gender	Male	0	0.95	1.32	1.74	4.08	1.38(0.60)
	Female	0	0.92	1.28	1.71	4.14	1.35(0.60)

Table 4-15 Quantile, mean and standard deviation of throughput of design-related variables for move touch

Variables	Levels	Quantile					Mean(SD)
		0%	25%	50%	75%	100%	
Target size (pixel)	36	0.01	1.30	1.72	2.19	4.14	1.77(0.65)
	70	0	0.94	1.28	1.63	2.86	1.30(0.48)
	106	0	0.72	1.02	1.31	2.14	1.02(0.39)
Target shapes	Circle	0	0.94	1.30	1.72	4.14	1.36(0.59)
	Rectangle	0.01	0.93	1.30	1.73	4.12	1.37(0.61)
Initial X (pixel)	60	0	0.94	1.29	1.71	4.14	1.36(0.59)
	180	0	0.93	1.31	1.73	3.92	1.37(0.61)
Initial Y (pixel)	80	0	0.92	1.28	1.71	4.12	1.35(0.60)
	210	0	0.94	1.31	1.74	4.14	1.38(0.60)
Final X (pixel)	60	0	0.93	1.30	1.73	4.08	1.37(0.60)
	180	0	0.94	1.30	1.72	4.14	1.36(0.60)
Final Y (pixel)	80	0	0.94	1.30	1.73	4.12	1.37(0.60)
	210	0	0.93	1.29	1.71	4.14	1.36(0.60)
Moving Direction	E	0	0.90	1.22	1.62	4.14	1.30(0.57)
	W	0.01	0.87	1.23	1.64	3.92	1.30(0.58)
	S	0	0.90	1.26	1.68	4.08	1.33(0.60)
	N	0	0.93	1.29	1.72	4.05	1.37(0.61)
	NE	0.10	1.05	1.42	1.86	3.51	1.48(0.61)
	NW	0	1.01	1.40	1.83	3.48	1.46(0.62)
	SE	0.02	0.98	1.35	1.76	3.50	1.41(0.59)
	SW	0.02	1.03	1.40	1.84	3.51	1.46(0.62)

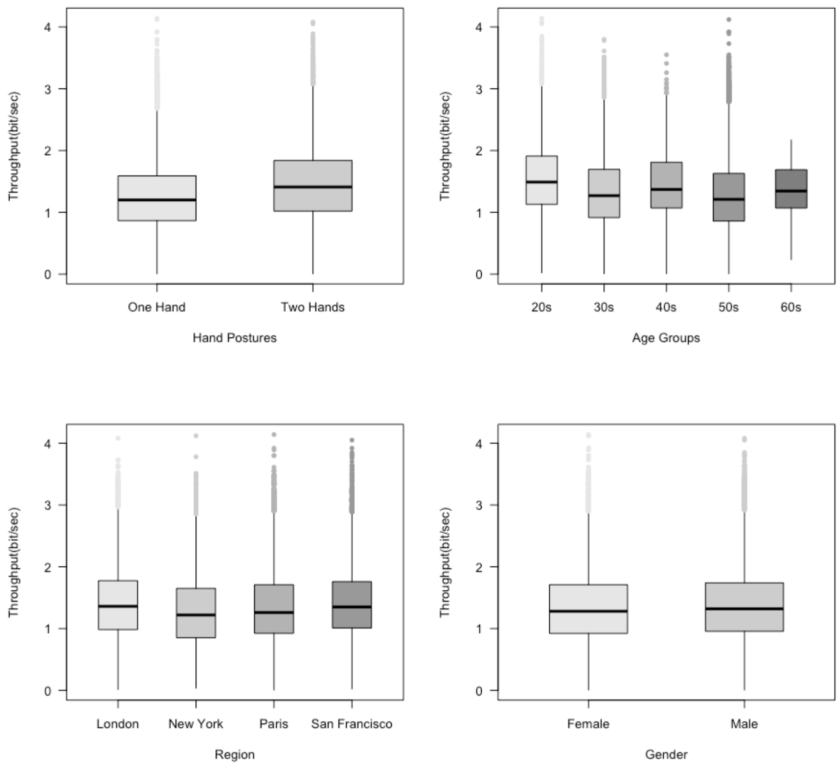

Figure 4-15 Boxplots of demography and interaction related variables regarding throughput for move touch

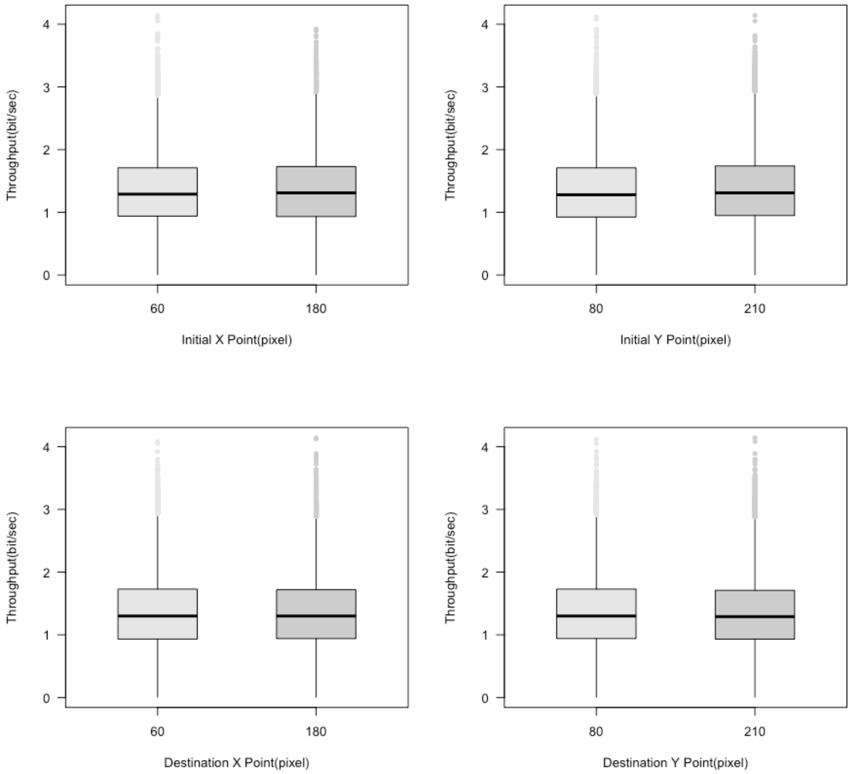

Figure 4-16 Boxplots of design-related variables regarding throughput for move touch. (regarding initial and destination points)

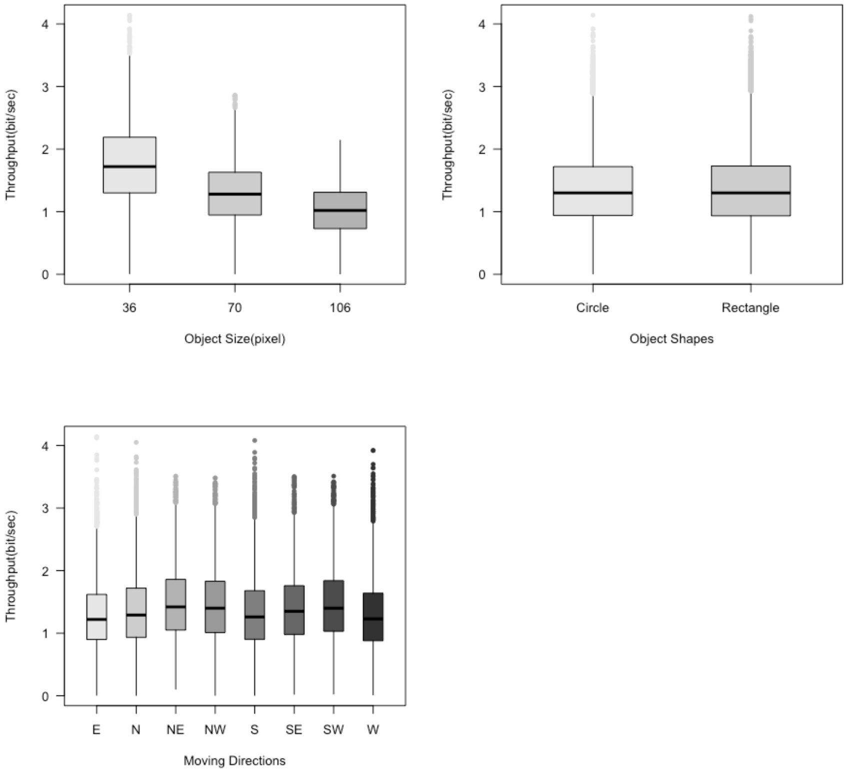

Figure 4-17 Boxplots of design-related variables regarding throughput for move touch. (object size, shape and moving directions)

Investigating effect size of each variable for throughput will allow us to identify how much of contribution of each variable affecting the performance. We can also investigate relative contribution amount by calculating the ratio of effect size. By order of percent contribution, target size(56.3%) showed the most value followed by age group(16.4%), hand(13.1%), movement direction(5.8%), region(5.6%), final Y(1.6%) and initial Y(1.3%). Initial and final X, target shape and gender showed 0% contribution. Among these variables, we have selected top 4 variables – target size(S), age group(A), hand(H) and movement direction(D) to be included in the final performance prediction model.

Table 4-16 Prediction model of throughput for move touch

	Estimated	Std Error	t-value	Pr(>|t|)
(Intercept)	2.217	0.018	117.580	< 2e-16***
S	-0.010	0.000	-74.549	< 2e-16***
A	-0.006	0.000	-21.063	< 2e-16***
H: Two hands	0.198	0.000	24.079	< 2e-16***
D: N	0.073	0.014	5.173	2.41e-07***
D: NE	0.194	0.017	11.166	< 2e-16***
D: NW	0.162	0.017	9.328	< 2e-16***
D: S	0.032	0.014	2.289	0.0221*
D: SE	0.110	0.017	6.312	3.03e-10***
D: SW	0.152	0.017	8.743	< 2e-16***
D: W	0.011	0.014	0.807	0.4197
Residual standard error: 0.2656 on 4160 degrees of freedom				
Multiple R-squared: 0.6218, Adjusted R-squared: **0.6209**				
F-statistic: 684.1 on 10 and 4160 DF, p-value: < 2.2e-16				

*** P-value < 0.001, ** P-value < 0.01, * P-value < 0.05

4.4 Conclusion and discussion

For move touch study, we have defined 4 distinctive performance measures – velocity from initial to final point, the accuracy of the initial touch point, the accuracy of final release point and throughput defined by Fitts (Fitts,1954) to get better understandings of affecting variables from three different groups – demography, design and task related. From ANOVA analysis and boxplots, it is identified that demographic variables are not critical in affecting performance measures. The object shapes are also less critical on performance compared to other variables.

It is identified that most the variables tested for this study showed statistical significance over performance measures, while this could be a little misleading due to the large volume of data thus high variability making data sensitive to statistical testing like ANOVA. We also looked into quantile, mean and SD along with boxplots for each variable to identify the extent of the contribution of each variable to performance measures.

4.4.1 Design strategy for one hand versus two hands

Better performance is observed on both velocity and throughput measures for two hands posture against one hand posture. From tap touch analysis, we observed that two hands postures showed longer task completion time, thus resulting in less velocity when the same distance is assumed. This is not conforming each other in terms of velocity measures. However, tap and move touch gestures require different levels of force exerted and movement strategy and goals. Move touch involves maintaining a certain level of force applied along the way of moving an object from initial point to target point where tap touch doesn't have this interaction. This may cause the difference in performance analysis in terms of one hand or two hands postures. Thus, each gesture should have its own predictive model and design guidelines in order to provide best performance level when we deal with a mixture of both gestures in design options.

4.4.2 Design strategy on moving direction

There are 8 moving directions used in this study – E/W/S/N/NE/NW/SE/SW. These moving directions are identified as less impacting factors for accuracy measures for initial touch points and final release points which are expected since initial touch point, and final release point may not contribute to the actual movement gestures. For both velocity and throughput, it is observed that diagonal directions show better performance than horizontal and vertical directions. Among diagonal directions, NE shows the best performance regarding throughput(1.48 bit/sec). NW and SW show the second best performance(both with 1.46 bit/sec) than SE(1.41 bit/sec). Though the differences among these directions are not significant in its amount, NE direction is the best direction to be considered when designing movement task for touch interface if performance matters.

4.4.3 Design strategy on object sizes

It is observed that task velocity, accuracy on initial touch and accuracy on final release all show increasing tendency as object size grows while throughput shows the opposite tendency. This is reasonable observation since throughput considers velocity factors(movement time and movement distance) and accuracy factor(object size). It is interesting to note that smaller target size shows higher throughput thus better expected performance from this study. Smaller target object shows better accuracy and slower velocity than larger targets. Even with this finding, throughput for smaller target shows higher than larger targets which could mean that velocity factor contributed less than accuracy factor in calculating throughput. From our study, smaller target sizes are recommended to use in move touch for better human performance.

4.4.4 Leveraging performance prediction models

Performance prediction models were established as in Table 4-4, Table 4-8, Table 4-12 and Table 4-16 for four performance measures. Most contributing variables were selected based on the percent amount of effect size of each variable. For task velocity, initial Y, final Y, age group, hand and movement direction were selected which yields adjusted the r-square value as 0.39. For accuracy of initial touch, initial X, age group, hand and gender were selected with adjusted r-square of 0.31. For accuracy of final release, final X, age group and hand were selected with adjusted r-square of 0.19. For throughput, target size, age group, hand and movement direction were selected with adjusted r-square of 0.62. It is worth to note that movement direction is not included for both accuracy measures since they don't expect to have much effect on those measures. Looking into variable selected for each measure, throughput may best represent from design and demography related variables along with highest adjusted r-squared value.

This result demonstrates that with the mixture of design-related variables and demographic variables, it is possible to predict each performance measures without conducting usability testing on design options. It will be an effective and efficient tool especially when comparing multiple design options to predict which one will demonstrate better performance rather than used as evaluating absolute usability measures.

Chapter 5. Flick touch experiment

5.1 Introduction

Flick touch is generally used for fast scrolling either horizontal or vertical list of items on a touch interface. Figure 5-1 shows screen examples on iPhone where flick touch gestures are used on iPhone screens.

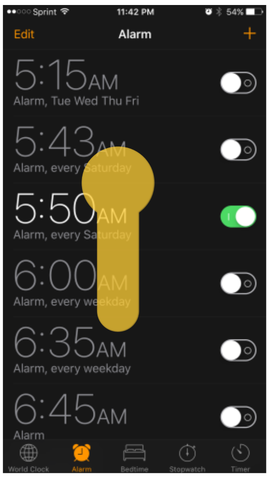

Figure 5-1 Example of flick touch on alarm list of iPhone

In the case of flick touch, specific starting point or release point is not presented on screen, rather user selects the start or release point of flick after moving a certain amount of distance. This is the main difference between move touch – move touch specifies the starting point and release point usually as screen element while flick touch doesn't show any screen element to guide users for the flick. What is common between flick and move touch is that it is composed of starting point, drag certain distance on screen, then release. Flick touch is considered as open loop control (Wright, & Smith, 1988) since its release point is not targeted or controlled.

As mentioned earlier, flick touch is generally super imposed on top of existing touch screen elements, it usually is not associated with specific touch elements on the touch screen. In that sense, design guideline for flick touch gesture would be more about flick distance, flick direction or flick duration time rather than dimensions of screen elements like size or shape as we investigated on tap touch experiment. Thus, in this study, we will be investigating flick travel distance, flick direction, flick duration time and accuracy of initial touch to see which variable affects the most to these performance measurements and what range of values would be suggested to achieve best flick touch performance. One could argue that since velocity implies travel distance and flick duration, it seems to make sense to use flick velocity to combine distance and duration. However, our goal is not to suggest flick velocity for best performance, rather to suggest optimal flick distance and duration, we will be looking each measurement separately instead of combining them into single measurement as flick velocity.

Thus, the goal of this study is to find optimal suggested values of flick distance, time and direction.

5.2 Method

5.2.1 Task design

Subjects were asked to flick the bar object presented on a display either up or down to complete the task and initial touch point, additional trajectory points and time to complete the task were recorded.

The input device had a 3.0-inch capacitive-type touch screen (Screen-to-Body Ratio: 51.7%, Resolution: 240×320 pixels), and its body size was 98mm×55mm×12.7mm with weight 100g. This is an identical device as in tap touch experiment.

The task interface was programmed on Microsoft Windows Mobile 6.1 platform. After a trial run, the log files were stored and retrieved in a text file format.

5.2.2 Experimental design

Figure 5-2 shows experimental setup for flick touch tasks. There are two levels of flick directions(up or down) and six levels of initial locations(55,90,125,160,195,230 in pixel) When initial flick target presented to the subject, required flick direction also presented on the display. Two different user postures(one hand and two hands) were also used for all task conditions.

The total number of experiments for a subject was 24(=2x6x2) which is calculated by multiplying all possible levels of the experimental setup for initial flick target(=6), flick directions(=2) and hand postures(=2). The order of the task conditions was programmed to come out in random order and logged accordingly. Since the subjects were asked to visit two separate days for three tasks, flick task was assigned either first or second visit of the subject. Since the volume of this task was not so large compared to other two tasks, it was conducted in a single day in a single session without rest.

The experiment was designed within-subject with a factorial design of input methods(2 levels : index finger and thumb), flick directions(2 ways) and initial locations(6).

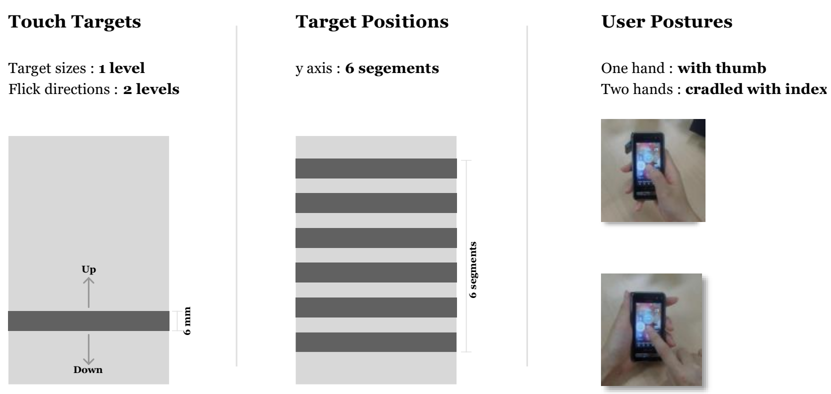

Figure 5-2 Experimental setups for flick touch tasks

5.3 Data analysis method

In order to answer established research questions for flick touch experiment, we investigated the 4 performance measures defined in previous section – flick task completion time(msec), flick travel distance(pixel), flick direction(degree) and accuracy of initial touch(pixel). From initial touch to final release, three in between trajectory points are also measured, so we have a total of 5 points from initial touch to final release. In order to measure the distance along with the trajectory of flick touch, the sum of distances of each point is calculated instead of from initial to final release.

First, we have conducted Anderson-Darling normality check, Q-Q plot and histogram for all performance measures to confirm normality of the data set. Then contributing factors are identified via ANOVA analysis for all experimental variables associated, and TukeyHSD test was used to analyze the effect (Abdi & Williams, 2010). Partial eta squared was calculated to investigate the effect size of each variable to performance measures (Kirk, 1982; Tabachnick, Fidell, & Osterlind, 2001; Levine, 2002). It quantifies the effect size of a factor in a factorial experiment by a proportion of the total variability attributable to the factor (Nandy, 2012). We used boxplots to investigate overall tendency or visual patterns of each variable, along with actual data point tables with quantiles, mean and standard deviations to confirm actual amount of pattern if there is any. Finally, with all identified critical variables to performance measures, we will derive regression models to establish performance prediction models for each performance measure.

5.3.1 Data handling

A total of 3,210 data points were gathered for right handed experiments only. We assumed that any finding from right handed use could be flipped to left handed use. In order to handle outliers, we used interquartile range method (Faraway, 2002; Zhao, 2012). This was applied to task completion time. This leaves us 2,901 data points about 9% reduction from initial data points.

Initial analysis indicated that individual variability needed to be addressed to increase the reliability of established model. In order to reduce inter-subject variability, we decided to aggregate data points as a single data point for each variable and level. This way, we reduced the number of data points down to 557 from initial 2,901.

5.4 Results

5.4.1 Normality check

We have conducted normality check on the performance measures for flick touch as we did on tap and move touch experiments.

Since we have a large volume of data for each measure, we cannot expect usual normality check like Anderson-Darling normality check or Q-Q plot(Figure 5-3) will conform normality of the data due to high variability caused by high volume of data. Figure 5-4 shows probability distribution of each performance variables – task completion time, travel distance, angle deviated from Y axis and offset from Y position. Task completion time seems closest to normal distribution based on probability distribution plot. While distance and deviation angle show left skewed distribution and offset Y shows right skewed distribution. We will assume normality of flick data set for the four performance measure variables according to these probability distribution plots. Note these plots are aggregated from all levels of variables.

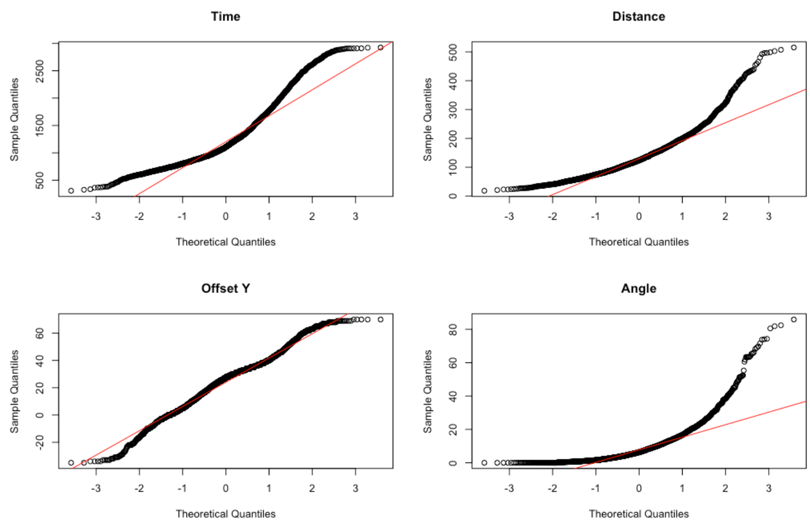

Figure 5-3 Anderson-Darling normality Q-Q plot for flick touch

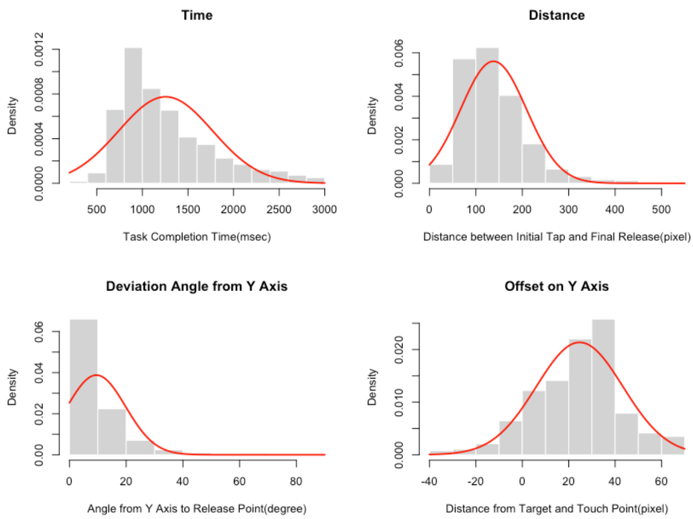

Figure 5-4 Probability distribution of time(msec), travel distance(pixel), deviation angle from Y axis(degree) and offset on Y axis(pixel)

5.4.2 Variables affecting task completion time on flick touch

Table 5-1 contains ANOVA result as well as the effect size of each variable on task completion time. We verified any data trend observed visually from Figure 5-5 and Figure 5-6 and quantile, mean and standard deviation values are presented in Table 5-2 and Table 5-3 for all levels of independent variables. Age group(A), region(R), gender(G) and Y position(Y) have statistically significant effect on task completion time for flick touch. Flick direction doesn't have an influence on task completion time. For variables statistically significant on task completion time, TukeyHSD test was conducted to investigate detail influences for each level of the variable.

Table 5-1 ANOVA and effect size(partial eta squared) of task completion time for flick touch

	η_p^2	Sum Sq	Df	F value	Pr(>F)
Hand(H)	0.005	206641	1	2.7555	0.097494
Age group(A)	0.213	11097588	4	36.9961	< 2e-16 ***
Region(R)	0.029	1208992	3	5.3739	0.001187**
Gender(G)	0.042	1812617	1	24.1709	1.168e-06***
Y Position(Y)	0.014	575416	1	7.6731	0.005796 **
Direction(D)	0.003	132428	1	1.7659	0.184447
Residuals		40870473	545		

*** P-value < 0.001, ** P-value < 0.01, * P-value < 0.05

As to age group, we cannot observe any increasing or decreasing tendency over age group at first glance on the data either boxplot or quantile values. It is spread from 1.0 sect to 1.3 sec on the average per age group. In order to look further into the difference among age group, we run TukeyHSD test to see pairwise effect among age group. From this test, it is observed that there is a significant difference between the 20s and 30s($p<0.001$), no difference between 30s and 40s, the difference between 40s and 50s($p<0.001$), and no difference between 50s and 60s. From this test result, we can see grouping among age group as the 20s as its own, 30s and 40s go together and 50s and 60s together. Thus, under these new three groups, we can observe increasing tendency over age group which conforms past research. Even though it is observed differences for each age group, the difference among groups are not granular rather blurry over ages so not so strong tendency over age groups.

As to regional difference, we also ran TukeyHSD test to see the detail differences. Average task completion time is decreasing from New York(1.3 sec), Paris(1.2 sec), San Francisco(1.2 sec) to London(1.1 sec). From the test, it is observed that there is no difference between New York and Paris, Paris and San Francisco, San Francisco and London. But the slight difference between New York and San Francisco(P adj=0.006), Paris and London(P adj=0.008). To sum up, even though ANOVA showed there are regional differences, we could conclude that regional difference is not that noticeable according to the TukeyHSD test result.

Male showed faster completion time than female group by 86 msec on the average. Even though this difference is subtle, it conforms with the findings that performance of simple movement task of the male group showed consistently better than female group (Baken, 1986; Barnsley & Rabinovitch, 1970; Fairbanks & Spriestersbach, 1950).

Among design-related variables, only Y positions showed a significant difference in the task completion time while flick direction doesn't from initial ANOVA analysis. However, from TukeyHSD test, it is observed that only 195-90 pair showed the significant difference which has longest(195, 1.31sec) and shortest(90, 1.18sec) task completion time among 6 task conditions.

All other pairs doesn't show any significance. Thus we could conclude that Y positions also don't have much effect on task completion time.

Table 5-2 Quantile, mean and standard deviation of task completion time(msec) of demography and interaction related variables for flick touch

Variables	Levels	Quantile					Mean(SD)
		0%	**25%**	**50%**	**75%**	**100%**	
Hand	One	337	890	1102	1515	2924	1261(523)
	Two	308	875	1109	1531	2920	1248(505)
Age group	20s	308	759	908	1135	2889	1010(397)
	30s	326	877	1079	1478	2908	1228(496)
	40s	617	868	981	1216	2690	1164(500)
	50s	337	978	1273	1702	2924	1389(530)
	60s	715	996	1027	1190	2585	1167(422)
Region	London	337	853	1005	1350	2924	1174(499)
	Paris	326	877	1102	1523	2906	1266(524)
	NY	308	932	1231	1658	2920	1343(533)
	SF	364	877	1109	1508	2907	1231(484)
Gender	Male	308	838	1050	1452	2920	1197(501)
	Female	326	902	1158	1558	2924	1294(520)

Table 5-3 Quantile, mean and standard deviation of task completion time(msec) of design-related variables for flick touch

Variables	Levels	Quantile					Mean(SD)
		0%	**25%**	**50%**	**75%**	**100%**	
Y Positions (pixel)	55	368	877	1074	1426	2889	1215(503)
	90	370	844	1043	1431	2920	1188(485)
	125	388	883	1109	1531	2907	1259(511)
	160	326	892	1128	1528	2924	1280(521)
	195	308	921	1173	1645	2909	1314(549)
	230	377	884	1085	1531	2880	1242(488)
Flick Directions	Up	370	877	1090	1487	2920	1242(506)
	Down	308	885	1122	1549	2924	1267(523)

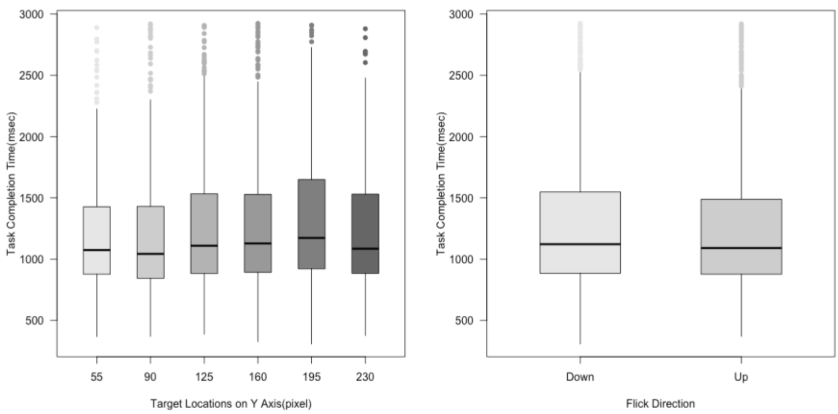

Figure 5-5 Boxplots of design-related variables regarding task completion time for flick touch.(Target location, Up/Down direction)

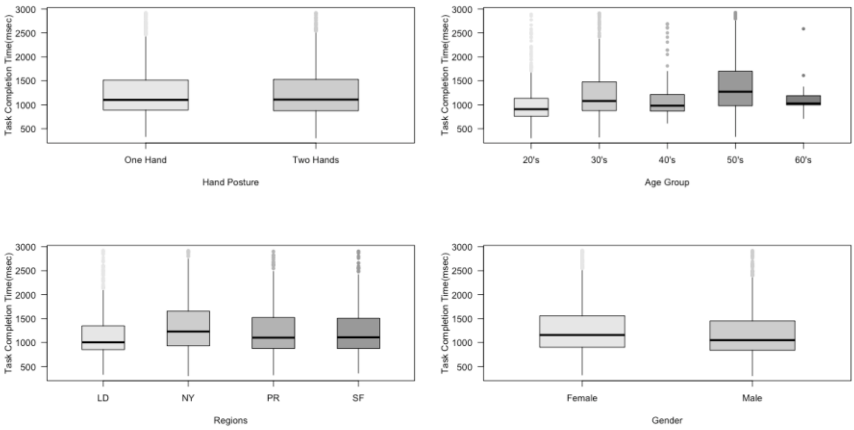

Figure 5-6 Boxplots of demography and interaction related variables regarding task completion time for flick touch.(Hand posture, Age, Region and Gender)

Investigating effect size of each variable for task completion time will allow us to identify how much of contribution of each variable affecting the performance. We can also investigate relative contribution amount by calculating the ratio of effect size. By order of percent contribution, age group(69.6%) showed the most value followed by gender(13.7%), region(9.5%), Y position(4.6%), hand(1.6%) and flick direction(1.0). Among these variables, age group(A), gender(G) and Y position(Y) were selected to be included in the final performance prediction model as depicted in the following Table 5-4.

Table 5-4 Prediction model of task completion time for flick touch

	Estimated	Std Error	t-value	Pr(>|t|)
(Intercept)	828.32	49.135	16.858	< 2e-16***
A	0.320	0.956	10.794	< 2e-16***
G: Male	-131.583	24.021	-5.478	6.55e-08***
Y	0.542	0.227	2.387	0.0173*
Residual standard error: 282.4 on 553 degrees of freedom				
Multiple R-squared: 0.2071, Adjusted R-squared: **0.2028**				
F-statistic: 48.15 on 3 and 553 DF, p-value: < 2.2e-16				

*** P-value < 0.001, ** P-value < 0.01, * P-value < 0.05

5.4.3 Variables affecting travel distance on flick touch

Table 5-5 contains ANOVA result as well as the effect size of each variable on the travel distance of flick touch. We verified any data trend observed visually from Figure 5-7 and Figure 5-8 and quantile, mean and standard deviation values are presented in Table 5-6 and Table 5-7 for all levels of independent variables. Hand posture(H), age group(A), Y position(Y) and flick directions(D) have statistically significant effect on the travel distance of flick touch. TukeyHSD test was conducted to investigate detail influences for each level of the variable.

Table 5-5 ANOVA and effect size(partial eta squared) of distance from initial touch and final release for flick touch

	η_p^2	Sum Sq	Df	F value	Pr(>F)
Hand(H)	0.009	8312	1	4.8638	0.0278432*
Age group(A)	0.079	79940	4	11.6936	4.059e-09***
Region(R)	0.002	1826	3	0.3562	0.7846732
Gender(G)	0.006	5375	1	3.1451	0.0767160
Y Position(Y)	0.017	16396	1	9.5935	0.0020533**
Direction(D)	0.025	24280	1	14.2065	0.0001817***
Residuals		931434	545		

*** P-value < 0.001, ** P-value < 0.01, * P-value < 0.05

The travel distance of two hands posture showed longer distance than one hand posture(8.85 pixels) which could be explained by the biomechanical constraints of one hand posture which will limit the range of motion of thumb, thus resulting in shorter flick distance while two hands posture doesn't have any restriction on the motion.

Though it is observed that age group has a significant effect on travel distance, by looking into TukeyHSD test, it is identified that there is slight significant different between the 30s and 40s($p<0.05$) and not between any of age group. Thus, we can conclude that age group impact on travel distance is negligible.

For gender, the male group tends to finish the flick movement earlier than the female group(6.2 pixels shorter on the average). This may be related to task completion time being shorter in the male group than female group. This could indicate that male group stress more on performance(thus speed) than accuracy compared to the female group.

It is observed that Y positions affect the travel distance of flick touch from ANOVA. In order to identify detailed segmentation, we looked into TukeyHSD test result on this variable. It is shown that travel distance is sorted by its increasing order from 230(163.19 pixels), 55(162.31 pixels), 195(140.42 pixels), 160(130.62pixels), 90(128.84 pixels) and 125(126.46 pixels). Among these groups, only 55-195 pair significantly different from the test. Thus we could identify two groups of positions – 230/55 and 195/160/90/125. It is interesting to note that top most and bottom most positions have the longest travel distances. Flick distance becomes longer when the flick start position is located closer to top or bottom of display, and shorter in between the two limits. It is not clear whether we could explain this with biomechanical constraints introduced by the location of target close to the edge or any kind of psychological influence by the fact that targets are too close to the edge of the screen thus mentally allocating more travel distance to complete the task.

For flick directions, the downward direction has longer travel distance than upward direction by 7.74 pixels on the average which is significantly different with P adj = 0.002. This may mean that flicking down poses less biomechanical restrictions in an upward direction.

Table 5-6 Quantile, mean and standard deviation of distance from initial touch and final release(pixel) of demography and interaction related variables for flick touch

Variables	Levels	Quantile					Mean(SD)
		0%	**25%**	**50%**	**75%**	**100%**	
Hand	One	18.3	83.0	118.8	166.8	507.2	133.8(71.2)
	Two	23.0	92.5	131.1	177.9	515.2	142.6(70.6)
Age group	20s	20.8	81.6	117.1	163.3	454.1	127.6(60.5)
	30s	23.0	92.5	131.1	177.9	515.2	136.7(72.5)
	40s	33.6	115.9	146.5	196.3	342.2	159.7(64.7)
	50s	18.3	89.8	128.3	176.0	507.2	142.5(74.4)
	60s	63.5	71.6	97.7	113.0	229.7	101.4(39.7)
Region	London	23.0	82.3	119.6	163.8	496.6	131.9(70.1)
	Paris	27.7	85.6	123.2	174.7	515.2	141.9(79.0)
	NY	20.8	91.1	127.3	170.8	498.7	138.7(67.5)
	SF	18.3	89.9	128.4	177.2	502.8	140.3(67.7)
Gender	Male	20.8	85.2	120.7	166.9	515.2	133.9(67.3)
	Female	18.3	89.2	126.8	176.1	502.8	140.8(73.4)

Table 5-7 Quantile, mean and standard deviation of distance from initial touch and final release(pixel) of design-related variables for flick touch

Variables	Levels	Quantile					Mean(SD)
		0%	**25%**	**50%**	**75%**	**100%**	
Y Positions (pixel)	55	30.4	111.1	154.5	214.5	403.9	162.3(70.9)
	90	28.0	78.3	113.1	165.2	502.8	128.8(73.3)
	125	18.3	85.8	117.1	156.0	515.2	126.4(60.4)
	160	23.0	89.2	121.8	152.9	458.4	130.6(63.1)
	195	24.1	85.9	121.7	173.6	507.2	140.4(75.4)
	230	23.7	106.2	163.0	202.1	498.7	163.1(79.4)
Flick Directions	Up	18.3	85.7	122.4	167.2	515.2	134.3(69.8)
	Down	23.0	89.5	126.4	177.0	507.2	141.8(72.1)

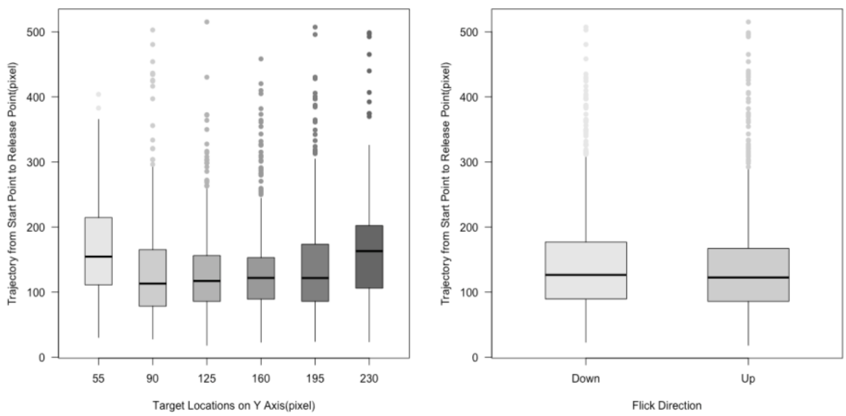

Figure 5-7 Boxplots of design-related variables regarding travel distance for flick touch. (Target location, Up/Down direction)

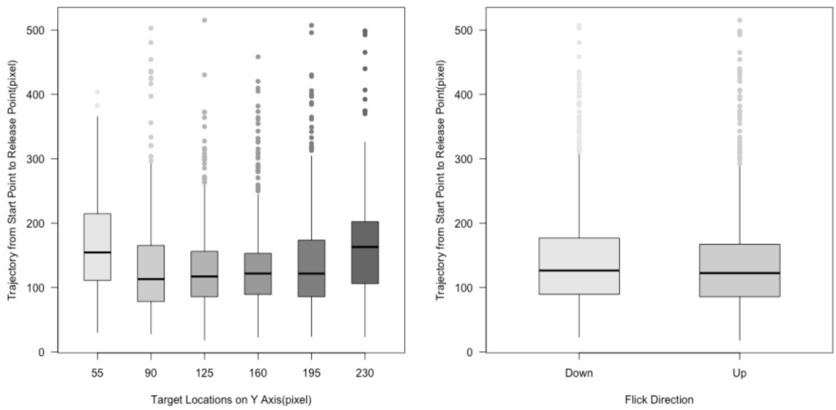

Figure 5-8 Boxplots of demography and interaction related variables regarding travel distance for flick touch.(Hand posture, Age, Region and Gender)

Table 5-8 Prediction model of travel distance for flick touch

	Estimated	Std Error	t-value	Pr(>|t|)
(Intercept)	114.629	7.307	15.686	< 2e-16***
A	0.416	0.145	2.869	0.004271**
Y	0.111	0.036	3.022	0.002630**
D: Up	-13.879	3.874	-3.582	0.000371***
Residual standard error: 42.94 on 553 degrees of freedom				
Multiple R-squared: 0.04287, Adjusted R-squared: **0.03768**				
F-statistic: 8.257 on 3 and 553 DF, p-value: 2.212e-05				

*** P-value < 0.001, ** P-value < 0.01, * P-value < 0.05.

Investigating effect size of each variable for travel distance will allow us to identify how much of contribution of each variable affecting the performance. We can also investigate relative contribution amount by calculating the ratio of effect size. By order of percent contribution, age group(57.2%) showed the most value followed by flick direction(18.1%), Y position(12.3%), hand(6.5%), gender(4.3%) and region(1.4%). Among these variables, only age group(A), Y position(Y) and flick direction(D) were included in the final performance prediction model as depicted in Table 5-8.

5.4.4 Variables affecting angle on flick touch

Table 5-9 contains ANOVA result as well as the effect size of each variable on the angle of flick touch. We verified any data trend observed visually from Figure 5-9 and Figure 5-10 and quantile, mean and standard deviation values are presented in Table 5-10 and Table 5-11 for all levels of independent variables. Hand(H), age group(A), region(R), gender(G) and flick direction(D) have statistically significant effect on an angle for flick touch.

Table 5-9 ANOVA and effect size(partial eta squared) of the angle from positive Y axis for flick touch

	η_p^2	Sum Sq	Df	F value	Pr(>F)
Hand(H)	0.101	1640.5	1	61.0450	2.888e-14***
Age group(A)	0.028	425.0	4	3.9532	0.003580**
Region(R)	0.028	417.6	3	5.1793	0.001552**
Gender(G)	0.063	976.5	1	36.3371	3.060e-09***
Y Position(Y)	0.000	4.3	1	0.1604	0.688908
Direction(D)	0.012	179.6	1	6.6831	0.009991**
Residuals		14646.6	545		

*** P-value < 0.001, ** P-value < 0.01, * P-value < 0.05

The angle of flick touch movement is measured to identify how much the flick trajectory deviates from Y axis. It is observed that angle of one hand posture showed greater value(11.36 degrees) than two hand postures(7.43 degrees). This means trajectory of flick movement of two hands posture is stiffer than one hand posture, thus closer to the vertical direction. This could be explained by thumb movement range of motion – abduction and adduction. Due to the biomechanical constraint of thumb movement, flick movement trajectory deviated more from the vertical line.

For regional impact, Paris, London and San Francisco are grouped together while New York showed the least value of the angle of the flick. Thus, participants from New York flicked most stiff than any other cities. All other cities showed larger angle value which may indicate that they were more under the effect of biomechanical constraints than New York. Though not clear, this might be explained by the difference in anthropometric difference in hand size or finger/thumb lengths – as it becomes bigger, it has a larger range of motion, thus less stiff angle for the flick movement.

For gender, the female group has a larger value of angle by 2.8 degrees which also may indicate that trajectory of female group is flatter than male group. This may be due to hand size difference – the male group tends to be bigger in their hand size, thus more possibility with a larger range of motion of hands than female group.

Y positions don't show any impact on the angle of flick trajectory while flick direction does($p<0.05$). Upward direction showed slightly flat trajectory than downward direction(0.83 degrees).

Table 5-10 Quantile, mean and standard deviation of the angle from positive Y axis(degree) of demography and interaction related variables for flick touch

Variables	Levels	Quantile					Mean(SD)
		0%	**25%**	**50%**	**75%**	**100%**	
Hand	One	0	3.3	8.2	15.6	85.8	11.3(11.5)
	Two	0	2.1	5.1	9.9	74.0	7.4(8.2)
Age group	20s	0	2.6	6.3	12.6	80.5	9.2(9.2)
	30s	0	2.6	6.3	12.7	68.2	9.0(9.2)
	40s	0	2.4	5.9	9.8	74.2	8.6(11.8)
	50s	0	2.7	6.3	13.3	85.8	9.9(11.2)
	60s	0	2.9	5.1	11.8	17.0	6.6(5.6)
Region	London	0	3.1	6.8	13.6	82.4	10.3(11.2)
	Paris	0	3.0	7.3	14.0	80.5	10.5(11.2)
	NY	0	2.2	5.2	10.5	68.2	7.9(8.4)
	SF	0	2.5	6.6	12.9	85.8	9.3(9.8)
Gender	Male	0	2.2	5.0	10.5	74.2	7.6(8.3)
	Female	0	3.0	7.5	14.4	85.8	10.7(11.2)

Table 5-11 Quantile, mean and standard deviation of the angle from positive Y axis(degree) of design-related variables for flick touch

Variables	Levels	Quantile					Mean(SD)
		0%	**25%**	**50%**	**75%**	**100%**	
Y Positions (pixel)	55	0	2.5	5.8	11.6	61.8	8.9(9.8)
	90	0	2.6	6.5	13.5	71.5	9.6(9.5)
	125	0	2.9	6.5	13.4	81.8	9.9(10.7)
	160	0	2.9	6.0	12.2	85.8	9.2(10.2)
	195	0	2.4	6.6	13.3	80.5	9.4(9.8)
	230	0	2.3	5.8	11.4	82.4	9.4(11.7)
Flick Directions	Up	0	2.9	6.9	13.3	85.8	9.9(10.5)
	Down	0	2.4	5.8	12.2	80.5	9.0(10.0)

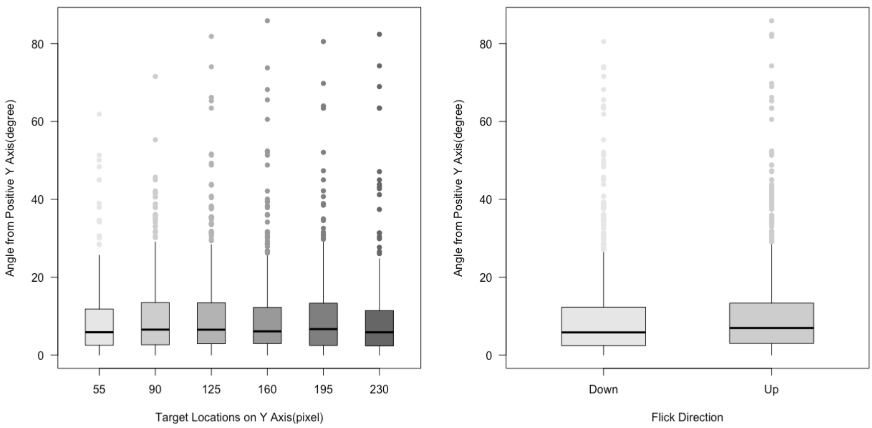

Figure 5-9 Boxplots of design-related variables regarding angle from Y axis for flick touch. (Target location, Up/Down direction)

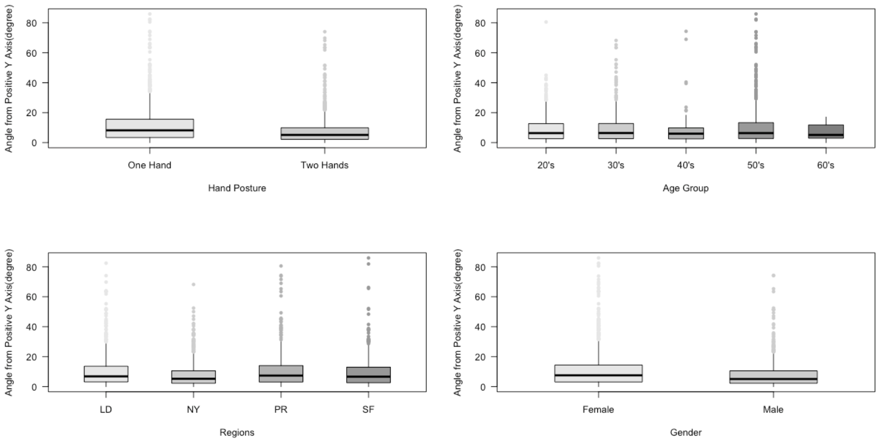

Figure 5-10 Boxplots of demography and interaction related variables regarding angle from Y axis for flick touch.(Hand posture, Age, Region and Gender)

Investigating effect size of each variable for an angle on flick touch will allow us to identify how much of contribution of each variable affecting the performance. We can also investigate relative contribution amount by calculating the ratio of effect size. By order of percent contribution, hand(43.5%) showed the most value followed by gender(27.2%), age group(12.1%), region(12.1%) and flick direction(5.2%) Among these variables, only Flick direction(D), gender(G) and hand(H) were included in the final performance prediction model as depicted in Table 5-12.

Table 5-12 Prediction model of angle from positive Y axis for flick touch

	Estimated	Std Error	t-value	Pr(>|t|)
(Intercept)	11.633	0.449	25.871	< 2e-16***
D: Up	1.158	0.446	2.594	0.00973**
G: Male	-2.857	0.447	-6.390	3.52e-10***
H: Two hands	-3.406	0.446	-7.625	1.07e-13***
Residual standard error: 5.271 on 553 degrees of freedom				
Multiple R-squared: 0.1606, Adjusted R-squared: **0.156**				
F-statistic: 35.26 on 3 and 553 DF, p-value: < 2.2e-16				

*** P-value < 0.001, ** P-value < 0.01, * P-value < 0.05

5.4.5 Variables affecting offset Y on flick touch

Table 5-13 contains ANOVA result as well as the effect size of each variable on an offset from Y position. We verified any data trend observed visually from Figure 5-11 and Figure 5-12. Hand(H), Y position(Y) and flick direction(D) have statistically significant effect on offset Y for flick touch. TukeyHSD test was conducted to investigate detail influences for each level of the variable.

Offset Y shows how much distance between target Y positions and actual touch position's Y coordinate, thus distance in the vertical direction. For demography and interaction related variables, we could not observe any impact on this value from ANOVA analysis.

Offset Y doesn't vary much based on the Y positions of the target. For flick directions, however, offset Y showed larger value for upward direction than downward direction by 16.82 pixels on the average. This means they intentionally miss hit the target towards the desired moving direction which is the upward direction in this case and vice versa for given downward flick direction.

Table 5-13 ANOVA and effect size(partial eta squared) of offset from target Y position for flick touch

	η_p^2	Sum Sq	Df	F value	Pr(>F)
Hand(H)	0.009	405	1	4.9338	0.02675*
Age group(A)	0.011	506	4	1.5405	0.18902
Region(R)	0.005	231	3	0.9375	0.42219
Gender(G)	0.000	2	1	0.0216	0.88332
Y Position(Y)	0.119	6018	1	73.2627	< 2e-16***
Direction(D)	0.552	55222	1	672.2283	< 2e-16***
Residuals		44771	545		

*** P-value < 0.001, ** P-value < 0.01, * P-value < 0.05

Quantile, mean and standard deviation values are presented in Table 5-14 and Table 5-15 for all levels of independent variables.

Table 5-14 Quantile, mean and standard deviation of offset from target Y position(pixel) of demography and interaction related variables for flick touch

Variables	Levels	Quantile					Mean (SD)
		0%	**25%**	**50%**	**75%**	**100%**	
Hand	One	-35	14	28	36	70	25.08(18.71)
	Two	-34	11	27	36	70	24.27(18.60)
Age group	20s	-34	11	27	35	69	23.89(17.99)
	30s	-35	12	27	35	70	23.97(18.23)
	40s	-31	14	29	37	66	25.96(18.62)
	50s	-35	13	28	36	70	25.40(19.27)
	60s	-3	21	27	36	49	26.70(13.27)
Region	London	-33	10	26	36	70	23.73(19.80)
	Paris	-34	15	29	37	70	26.04(19.14)
	NY	-35	14	27	34	70	24.52(16.61)
	SF	-35	12	27	36	70	24.72(19.10)
Gender	Male	-34	12	26	35	70	24.37(18.11)
	Female	-35	12	28	36	70	24.92(19.03)

Table 5-15 Quantile, mean and standard deviation of offset from target Y position(pixel) of design-related variables for flick touch

Variables	Levels	Quantile					Mean(SD)
		0%	**25%**	**50%**	**75%**	**100%**	
Y Positions (pixel)	55	-27	8	23	33	65	21.0(16.3)
	90	-34	17	30	39	70	28.1(18.2)
	125	-35	12	25	35	69	23.9(19.3)
	160	-35	10	25	36	70	23.0(19.7)
	195	-34	11	29	36	70	24.0(19.8)
	230	-22	20	29	35	68	27.9(13.6)
Flick Directions	Up	-31	27	33	41	70	33.7(14.8)
	Down	-35	3	16	28	69	15.5(17.6)

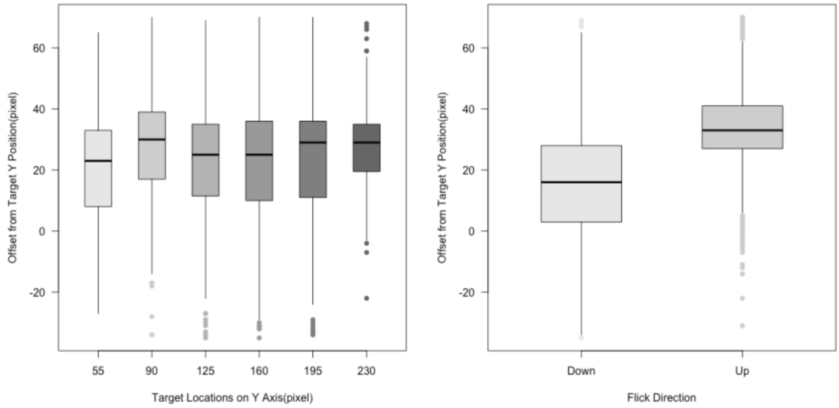

Figure 5-11 Boxplots of design-related variables regarding offset Y for flick touch

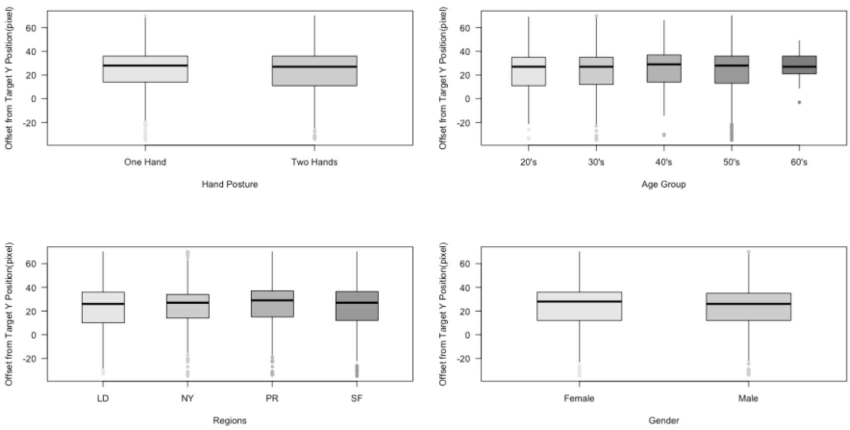

Figure 5-12 Boxplots of demography and interaction related variables regarding offset Y for flick touch. (Hand posture, Age, Region and Gender)

Investigating effect size of each variable for offset Y on flick touch will allow us to identify how much of contribution of each variable affecting the performance. We can also investigate relative contribution amount by calculating the ratio of effect size. By order of percent contribution, flick direction(79.3%) showed the most value followed by Y position(17.1%), age group(1.6%), hand(1.3%) and region(0.7%) Among these variables, only Flick direction(D) and Y position(Y) were included in the final performance prediction model as depicted in Table 5-16.

Table 5-16 Prediction model of offset from target Y for flick touch

	Estimated	Std Error	t-value	Pr(>|t|)
(Intercept)	23.418	1.116	20.978	< 2e-16***
D: Up	21.193	0.821	25.789	< 2e-16***
Y	-0.066	0.007	-8.498	< 2e-16***
Residual standard error: 9.109 on 554 degrees of freedom				
Multiple R-squared: 0.5456, Adjusted R-squared: **0.544**				
F-statistic: 332.6 on 2 and 554 DF, p-value: < 2.2e-16				

*** P-value < 0.001, ** P-value < 0.01, * P-value < 0.05

5.5 Conclusion and discussion

For flick touch study, we have defined 4 distinctive performance measures – task completion time(msec), travel distance from initial touch point and final release point(pixel), angle from Y axis(degree) and offset from target Y position to get better understandings of affecting variables from three different groups – demography, interaction and design related. From ANOVA analysis and boxplots, it is identified that regions and age groups are not critical in affecting performance measures defined. Hand postures showed some impact on travel distance and angle from Y axis. Gender also showed some different levels of performance for task completion time, travel distance and angle from Y axis. Interestingly, Y positions only showed the impact on travel distance - top most and bottom most positions. Flick direction showed the impact on the angle from Y axis and offset Y.

We have used ANONA analysis to initially screen variables affecting performance measures then ran TukeyHSD to see further details in interacting terms. Quantile, mean, standard deviation tables were presented to demonstrate the details of dataset gathered along with associated boxplots to allow us visual comparison and assessment on each variable.

5.5.1 Design strategy on demography and interaction related variables for flick movement

In general, demography and interaction related variables are difficult to control when designing touch interface since they are considered as independent variables rather than controllable dependent variables. However, from the findings we got from our study, we could at least provide some minimum guidelines when designing touch interface.

As we noticed from the previous section, regions and age group don't show the critical impact on performance measures we defined. Hand postures do show the impact on travel distance and angle from Y axis. For travel distance, one hand posture showed shorter distance(25.4mm) than two hands posture(27.1mm). In terms of an angle from Y axis, one hand posture showed 11.35 degree while two hands posture showed 7.43 degree. From posture perspective, in order to cover the most use cases of hand postures, it is recommended to provide clearance on touch area at least 27.1mm distance and up to 11.35 degree from Y axis. This is a pie shaped area on both directions either upward or downward. We also observed a significant difference in distance and angle for gender, where male group showed 25.4mm in distance and 7.69 degrees in angle and female group as 26.67mm in distance and 10.71 degrees in angle. As we can see, these ranges are covered when we provide clearance of other touch interfaces within 27.1mm and 11.35 degree range. Thus we don't need to be concerned about hand postures and gender difference if we can secure this flick area.

5.5.2 Design strategy on design-related variables for flick movement

From previous analysis, it is interesting to note that Y positions affect on travel distance and angle from Y axis, and flick direction only on the angle from Y axis and offset Y. Since Y position showed significant difference only at the either edge of positions – top and bottom, which produced longer flick distance than on any other Y positions, it is recommended to avoid putting initial flick positions close to the edge of the screen either on top or bottom. More specifically, we observed significant distance increase at position 55 and 230, which are around 10mm off from the edge of the display. Assuming actual threshold of this increase lies somewhere in between position 55 and 90, it is safe to assume that we would need to secure at least 17mm off from the edge of the screen either from top or bottom. Also, if we consider previous recommendation based on observed average travel distance, it is best to secure at least 27mm off from screen edges to place the starting point of flick movement.

In terms of offset Y, upward direction showed more displacement from the target position, 33.76 pixels on the average. In order to cover 95% of offset, we could consider providing target height of mean+2SD, which is around 12mm. This covers almost 100% of accuracy from tap touch result recommendation.

5.5.3 Leveraging performance prediction models

Performance prediction models were established as in Table 5-4, Table 5-8, Table 5-12 and Table 5-16 for four performance measures. Most contributing variables were selected based on the percent amount of effect size of each variable. For task completion time, age group, gender and Y position were selected which yields adjusted the r-square value as 0.20. For travel distance, age group, Y position, and flick direction were selected with adjusted r-square of 0.04. For angle, flick direction, gender and hand were selected with adjusted r-square of 0.16. For offset Y, flick direction and Y position were selected with adjusted r-square of 0.54.

This result demonstrates that with the mixture of design-related variables and demographic variables, it is possible to predict each performance measures without conducting usability testing on design options. It will be an effective and efficient tool, especially when comparing multiple design options to predict which one will demonstrate better performance rather than used as evaluating absolute usability measures.

Chapter 6. Conclusion

6.1 Research goals

This study aims to answer the following research questions for three most commonly used touch gestures for touch interface systems – tap, move and flick touch. 1) What are the variables affecting the performance measures defined and how much are they contributing? 2) Is there a way to establish design guidelines which provide expected performance measure per design specifications without conducting performance validation experiment every time interface system implemented?

In chapter 3 to chapter 5, we have identified contributing variables for each performance measure of touch gesture by analyzing experimental data.

The ultimate goal of this research is to provide comprehensive design guidelines to help system architects or user experience designers build touch interface system with the minimal amount of time and effort for usability validation.

By analyzing mostly commonly use touch gestures, almost all kind of interaction task can be evaluated or design using design strategies and data gathered in this study.

6.2 Summary of findings

Regarding tap touch gesture, we have investigated 4 performance measures (task completion time, the accuracy of tap touch, the angle from positive X axis, and speed accuracy ratio) across 8 independent variables(hand, age group, gender, region, target X, target Y, target size, target shape). By analyzing experimental data, we have identified increasing or decreasing tendency observed in task completion time for target sizes, age groups, gender, hand and positions on the display.

Accuracy measure also showed a tendency on one-hand versus two-hands setup, target sizes and positions.

Angles to touch center showed that on the average, subjects tend to touch on third quadrant relative to the center of touch target in general. After identifying typical tap area in quadrants, design guideline was suggested.

Speed accuracy ratio showed that one hand setup prioritizes speed over accuracy while two hands setup prioritizes accuracy over speed. The same tendency was observed in terms of target sizes, as target size grows, movement strategy put more stress on speed over accuracy.

We also have identified expected performance (probability of getting tap target successfully) across different sizes of tap targets. Leveraging this information, we will be able to predict overall performance of tap targets in terms of success rates so that we can evaluate any touch interface system by just measuring their effective target size.

For move touch, it is identified that one hand and two hands setup contributed the most difference in terms of throughput. The performance of two hands setup showed 14% better performance on the average. In terms of design-related variables, it showed that smaller tap target demonstrated better performance over the bigger target. However, what is more, critical to move touch performance is from moving directions. In general, diagonal movements performed better than vertical or horizontal directions. Thus it is recommended to consider design movement directions as diagonal rather than rectilinear. This tendency is observed for both one hand and two hands setup so we cannot conclude that this is related to biomechanical constraints posed by one hand posture. Rather, we can say that human fingers perform better when moving diagonal directions than rectilinear directions.

For flick touch study, we have defined 4 distinctive performance measures – task completion time(msec), travel distance from initial touch point and final release point(pixel), angle from Y axis(degree) and offset from target Y position to get better understandings of affecting variables from three different groups – demography, interaction and design related. From our analysis, it is identified that regions and age groups are not critical in affecting performance measures defined. It is shown that travel distance ends earlier for one hand setup than two hands setup which we assumed it is due to biomechanical constraints posed by posture.

We also suggested how much flick space need to be secured in terms of flick distance upward and downward, and flick directions. Since flick touch is provided on top of existing touch elements, this suggestion is about how to implement invisible touch area rather than guidance on tangible touch elements like tap or move touch experiments.

6.3 Performance prediction models

Performance prediction models were developed for all performance measures regarding all three touch gestures. These models are expected to be leveraged for relative comparison of touch performance across different design options. This will help designers save time and effort to conduct formal or informal usability testing to estimate the performance level of each option thus contribute to foster the timely development of interface system with minimal resource investment.

6.4 Limitations and future studies

In this study, we have used demography related variables such as regions, gender and age. We have identified certain tendency over these variables across different performance measures for each experiment. For example, accuracy difference between the male and female group, performance degradation over age groups while they are getting older groups. These are useful findings in designing touch interface systems especially when target audience group is gender specific or age group specific. However, in providing more generic design guidelines for users, anthropometric data would have been useful to consider in analyzing experimental results. Since we generally didn't see much regional differences across 3 touch studies, if we could have achieved anthropometric data – specifically hand and finger size data, then we could have established more solid modeling or provide specific design guidelines for touch interface implementation.

Along with anthropometric data, it would be valuable to investigate factors affecting human performance in touch interface in terms of device sizes. Device size used for this experiment is relatively small than the ones popular in the market today. If we could identify performance difference with different size devices, we could have also come up with performance modeling according to device sizes. This finding would be specifically useful for one-hand setup than two-hands setup.

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Abstract (in Korean)

터치 인터페이스는 지난 10여년간 스마트폰의 주요한 인터페이스 시스템으로 진화해 왔다. 이러한 현상은 비단 스마트폰에만 해당하지 않고, 휴대용 디지털 기기 전반에 걸쳐 진행되어 왔으며, 최근에는 마이크로소프트의 최신 윈도우즈 운영체제에 기존의 마우스 포인터를 이용한 인터페이스와 함께 터치 인터페이스가 함께 적용 되는 등 그 적용 영역이 점점 넓어지고 있는 추세이다.

터치 인터페이스를 설계하고 이용함에 있어서 사용자의 능력 혹은 사용성을 평가하기 위한 수많은 연구가 지속되어 왔다.이러한 연구 결과들은 터치인터페이스를 디자인하거나 개발하는 팀 혹은 조직에 유용하게 사용되는 결과를 제공할 수 있다. 이러한 연구들의 결과물은 터치 인터페이스의 기본적인 특성을 이해할 수 있도록 도와주며, 그를 바탕으로 보다 사용하기 편하고 효율적인 시스템 설계를 가능하게 할 수 있다. 이렇게 확보된 사용성과 효율성은 특히 디지털 기기를 개발/생산/판매 하는 조직이나 회사에게 경쟁 우위를 제공할 수 있는 중요한 기회 요소가 될 수 있다.

본 연구에서는, 이러한 터치 인터페이스의 사용성과 효율성에 영향을 미치는 변수들을 알아 보기 위하여, 세 그룹의 변수들을 선정하여 실험을 진행하였다. 첫번째 변수 그룹은 나이,성별,출신지역 등 인구통계학적인 변수들이며, 두번째 변수 그룹은 왼손/오른손 잡이, 한손/양손 사용 등 시스템과 상호 작용하는 것과 연관 있는 변수 들이다. 마지막으로 타겟의 크기나 위치, 움직이는 방향등과 같이 디자인으로 통제가 가능한 변수들이며, 이러한 세 그룹의 변수들이 실험에 사용되었다.

본 연구에 사용된 터치 제스쳐는 탭, 무브, 플릭의 세가지 종류이며, 이 제스쳐들은 터치 인터페이스 시스템에 널리 사용되는 기본적인 제스처들이므로, 이에 대한 이해를 확보할 수 있다면 대부분의 터치 제스쳐에 대한 이해 또한 유추할 수 있을 것으로

기대된다. 이를 위해, 3개국 4개 대도시(뉴욕,샌프란시스코,런던, 파리)에서 총 259명의 사용자를 섭외하여 각각의 터치 제스쳐에 대하여 반복 실험을 수행하였다.

터치 제스쳐의 사용성 및 효율성을 측정하기 위하여, 각각의 터치 제스쳐에 대한 성능 변수를 정의하여 계산하였고, 이에 대한 분석을 통해 각 터치 제스쳐의 특성을 파악하였다.

본 연구의 목적은 터치 인터페이스의 사용성 및 효율성에 영향을 미치는 변수들을 실험을 통해 확인하고 터치 인터페이스에 이러한 변수들이 미치는 영향을 수치화하고, 이를 기반으로 최적의 터치 인터페이스를 설계 할 수 있는 디자인 가이드라인 및 디자인 전략을 제시하는데에 있다.

본 연구의 결과를 이용하여, 기 디자인된 터치 시스템의 디자인 변수들을 확인함으로써, 기 분석된 성능 데이터 모델에 대입하여 대략적인 성능 평가 결과를 확인할 수 있으며, 이를 통해 디자인 평가에 소요되는 비용과 시간을 절감할 수 있는 효과를 제공할 수 있다.

주요어: Touch, Gesture, Smart device, Human performance, Design, Guideline

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